SAFETY IMPACTS OF DESIGN EXCEPTIONS IN UTAH

by

Jonathan Sayre Wood

A thesis submitted to the faculty of
The University of Utah
in partial fulfillment of the requirements for the degree of

Master of Science

Department of Civil and Environmental Engineering

The University of Utah

December 2012

The University of Utah Graduate School

STATEMENT OF THESIS APPROVAL

The thesis of **Jonathan Sayre Wood**

has been approved by the following supervisory committee members:

Richard Jon Porter, Chair **10/18/12** Date Approved

Xuesong Zhou, Member **10/18/12** Date Approved

Lawrence Reaveley, Member Date Approved

and by **Chris Pantelides**, Chair of

the Department of **Civil and Environmental Engineering**

and by Charles A. Wight, Dean of The Graduate School.

ABSTRACT

The objective of this research was to compare safety, measured by expected crash frequency and severity, on road segments where design exceptions were approved and constructed to similar road segments where no design exceptions were approved or constructed. Data were collected for design exceptions in Utah in the years 2001 through 2006. Design exception request and approval forms, Google Earth, Google Street View, UDOT functional classification maps, and UDOT traffic volume data were used to identify and define road segments with and without design exceptions. Ultimately, a total of 48 segments with design exceptions and 132 segments without design exceptions were used for modeling. Propensity scores were applied in this study to assess the comparison sites (i.e., sites without design exceptions). The relationship between design exception presence and crash frequency was explored using a negative binomial regression modeling approach. The relationship between design exception presence and crash severity was explored in three ways: 1) computing severity distributions at locations with and without design exceptions, and 2) estimating separate negative binomial regression models by severity level. Design exception presence was represented in the regression models by an indicator variable (1 = one or more design exceptions; 0 = no design exceptions). Crash data from the years 2007 through 2010 were used for model estimation. Road segments with one or more design exceptions had the same expected

frequencies of total crashes (all types and severities), fatal-plus-injury crashes, and property-damage-only crashes as road segments without design exceptions.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS

AADT	Average Annual Daily Traffic
AASHTO	American Association of State Highway and Transportation Officials
CMF	Crash Modification Factor
DOT	Department of Transportation
FHWA	Federal Highway Administration
NHS	National Highway System
PDBS	Project Development Business System
RE	Resident Engineer
SPF	Safety Performance Function
STRAHNET	Strategic Highway Network
UDOT	Utah Department of Transportation
HSM	Highway Safety Manual

INTRODUCTION

Problem Statement

Designs and plans for construction and reconstruction projects on state facilities are created using state-agency-adopted geometric design criteria. UDOT has adopted A Policy on Geometric Design of Highways and Streets (Green Book) as its standard for roadway design with some differences noted in the UDOT Roadway Design Manual of Instruction *(1) (2)*. Meeting established design criteria is not always practical or cost-effective. Deviating from design criteria requires documentation and approval. This generally occurs at two levels within UDOT: design exceptions and design waivers. Design exceptions are prepared when a road design deviates from one or more of the FHWA 13 controlling design criteria. Formal review and approval is required for design exceptions on an NHS or STRAHNET construction or reconstruction project. Project costs with the design exception(s) are estimated and compared to project costs if the 13 controlling criteria are met *(3)*. The FHWA, *Federal-Aid Policy Guide* states that an "exception should not be approved if the exception would result in degrading the relative safety of the roadway" *(4)*. Predicting the potential safety consequences of design exceptions is challenging, and only two studies were identified where an attempt was made to "track" safety of road segments where design exceptions had been approved *(5) (6)*. Design waivers are the UDOT equivalent of design exceptions for selected design elements other than the 13 controlling criteria. Examples of design elements for design waivers are side slopes, acceleration lane length, curb configuration, and rumble strips. Design exceptions are the focus of this research.

A recent survey of transportation agencies revealed that design exception application processes for most states included safety assessments of the proposed exceptions; the types of safety analyses varied substantially between states and relatively little was known about actual, quantitative safety impacts of design exceptions *(7)*. The AASHTO *Highway Safety Manual* (HSM) was intended to fill this void, but a significant amount of safety information related to the FHWA controlling criteria was not included in the first edition *(8)*. Research to assess the safety impacts of design exceptions was needed. The results of this project will provide insights into the effectiveness of the current UDOT design exception preparation and approval process. Results also create additional documentation that includes an evaluation of designs resulting from design exceptions. The research methods are adaptable to other states for DOTs interested in conducting similar evaluations.

Objectives

The objective of this research was to compare safety, measured by expected crash frequency and severity, on road segments where design exceptions were approved and constructed to safety on road segments with similar characteristics where no design exceptions were approved or constructed.

Scope

The research objectives were met by accomplishing eight research tasks. Road segments where design exceptions were approved and the resulting design constructed were identified and defined in Task 1. Traffic, geometric, and other key characteristics for these road segments were then collected (Task 2). The number and severity of crashes occurring on the road segments defined in the first two tasks was determined in Task 3. Crash data spanning the years 2007 through 2010 were used for analysis. Similar road segments to those defined in Task 1, but without design exceptions, were defined in Task 4. These segments made up the comparison group. The adequacy of the comparison group was assessed using propensity scores. Traffic, geometric, and other key characteristics for these comparison road segments were then collected (Task 5) and the number and severity of crashes occurring on these road segments defined (Task 6). Expected crash frequency and severity of road segments where design exceptions were approved were compared to the expected crash frequency and severity of similar road segments where no design exceptions were approved in Task 7. The entire study was then documented (Task 8).

The study looked at the safety effects of design exceptions at an aggregate level (freeway and nonfreeway road segments) and on nonfreeway road segments. The safety effects of exceptions to individual design criteria or specific combinations of design criteria were not explored in detail due to limited sample sizes. The analysis focused on all crash types, by severity level. Specific crash types (e.g., single-vehicle, run-off-road; same-direction-sideswipe) were not explored. The study was not intended to recommend any new additions or modifications to UDOT design exception policy. It was intended to provide insights into the effectiveness of the current design exception preparation and approval process from a safety perspective. UDOT and the Mountain Plains Consortium jointly sponsored a significant portion of the work documented in this thesis. Final research reports were published as *(9) (10)*. This thesis builds on this sponsored work by UDOT and the Mountain Plains Consortium. The crash data and models for the final research reports used crash data from 2006-2008. The crash data used in this thesis were from 2007-2010. This thesis also covers more details of the research and statistical theory. Updated results using newer and more crash data are also presented. From this work, a paper on the safety impacts of design exceptions on nonfreeway road segments has been submitted to the Transportation research Board for presentation and publication. Also, a paper on the theory and application of propensity scores in transportation research is planned for submittal to be published in a journal based on the work in this thesis.

BACKGROUND

Overview

State DOTs develop designs and prepare plans for road construction. Designers are guided by a set of state-adopted standards and policies that include design criteria. Design criteria are based on research and practice, and are generally expressed as minimums, maximums, or ranges of values for design elements (e.g., minimum horizontal curve radius, maximum grade). Individual state DOTs, as well as AASHTO, consider factors such as safety, efficiency, driver comfort, aesthetics, construction cost, and future maintenance activities when adopting or recommending design criteria. Meeting all design criteria is not always possible or practical. There are cases where meeting all design criteria would result in significant environmental impacts, community impacts, and/or construction costs. When this occurs, a design exception may be explored as an alternative. A design exception is the process and resulting documentation associated with a geometric feature created or perpetuated by a highway construction project that does not conform to the criteria set forth in design standards or policies *(7)*. The term design exception is sometimes used only when referring to one or more of FHWA's following controlling criteria:

1. Design speed
2. Lane width
3. Shoulder width

4. Superelevation
5. Horizontal alignment
6. Grade
7. Cross slope
8. Stopping sight distance
9. Structural capacity
10. Bridge width
11. Vertical clearance
12. Horizontal clearance
13. Vertical alignment

Terms such as “design variance” or “design waiver” are sometimes used when referring to other design criteria. A design exception requires formal review and approval if the construction project is on the NHS and the design criterion (or criteria) is among the 13 controlling criteria.

The controlling criteria are identified in the *Federal-Aid Policy Guide (4)* and described in *Mitigation Strategies for Design Exceptions (11)*. State adopted design criteria for NHS construction or reconstruction projects must be at least “as great as” values in AASHTO’s Green Book and AASHTO’s *A Policy on Design Standards – Interstate System* for these elements *(1) (12)*. UDOT has adopted the Green Book along with other relevant AASHTO guides as its standard for roadway design with some differences noted in the UDOT *Roadway Design Manual of Instruction (2)*. The minimum values for the 13 controlling criteria set forth by the Green Book (interpreted for Utah conditions) and by the UDOT *Roadway Design Manual of Instruction* are shown in Tables 1 through 3. The minimum criteria values set by UDOT are sometimes larger (or smaller for maximum values) than the values in the Green Book. A few examples include:

1. Vertical clearance for UDOT is 16.5 ft minimum for all functional classifications. The Green Book minimum values range from 14 ft to 16 ft.
2. Superelevation for UDOT has a maximum value of 6%. The green book allows for up to 8% for Utah conditions.
3. Cross slope is required to be 2% by UDOT. The green book allows 1.5 – 2.5%.

Some states have identified additional controlling or critical criteria, considered equal in importance to the 13 identified above, such as intersection sight distance and clear zones. State DOTs also prepare design exceptions for other design criteria. These supplemental criteria that are currently used by more than one state DOT include cut/fill slopes, roadside features (including culverts), median width, guardrail, design level of service, median opening spacing, intersection sight distance, and ramp acceleration and deceleration lane lengths *(7)*.

A recent survey of state DOTs identified benefits, problems, and potential improvements associated with design exceptions *(7)*. Almost all DOTs surveyed viewed design exceptions, and the resulting documentation of the associated decision process, as valuable. Reported difficulties included lack of supporting quantitative information, inadequate guidance on controlling criteria definitions and applications, and resource requirements (e.g., agency personnel, funds, and time). The potential safety implications of design exceptions are a central issue to design exception review and approval, but documentation of the process by which safety is considered varied from state to state *(7)*.

Table 1 Minimum design requirements for freeways

Criteria	Freeways	
	Green Book	UDOT
Design Speed	50-75 mph Not less than posted/proposed posted speed and as high as is reasonable	Same as Green Book
Lane Width	12 ft	12 ft
Shoulder Width	10 ft	10 ft
Superelevation	As needed up to 8%	As needed up to 6%
Horizontal Alignment	Meet minimum for design speed	Same as Green Book
Grade	3-6% Maximum 0.5% Minimum	3-6% Maximum 0.5% Minimum
Cross Slope	1.5-2.5%	2%
Stopping Sight Distance	Meet minimum for design speed	Same as Green Book
Structural Capacity	HS 20-44	HS 20
Bridge Width	Same Width as Roadway	Same as Green Book
Vertical Clearance	16 ft	16.5 ft
Horizontal Clearance	10 ft (to median barrier) 4 ft (to median barrier - 4 lane freeway only) 12 ft (to outside barrier)	Same as Green Book
Vertical Alignment	Meet Stopping Sight Distance Requirement	Length ≥ 1,000 ft Meet Stopping Sight Distance Requirement

Table 2 Minimum design requirements for arterials

Criteria	Arterials			
	Rural		Urban	
	Green Book	UDOT	Green Book	UDOT
Design Speed	40-75 mph Not less than posted/proposed posted speed and as high as is reasonable	Same as Green Book	30-60 mph Not less than posted/proposed posted speed and as high as is reasonable	Same as Green Book
Lane Width	12 ft	12 ft	12 ft	12 ft
Shoulder Width	4-8 ft	4-8 ft	4-8 ft	4-8 ft
Superelevation	As needed up to 8%	As needed up to 6%	As needed up to 6%	As needed up to 4%
Horizontal Alignment	Meet minimum for design speed	Same as Green Book	Meet minimum for design speed	Same as Green Book
Grade	3-8% Maximum 0.5% Minimum	3-8% Maximum 0.5% Minimum	5-11% Maximum 0.5% Minimum	5-11% Maximum 0.5% Minimum
Cross Slope	1.5-2%	2%	1.5-3%	2%
Stopping Sight Distance	Meet minimum for design speed	Same as Green Book	Meet minimum for design speed	Same as Green Book
Structural Capacity	HS 20-44 if NHS	HS 25 or HL 93	None	HS 25 or HL 93
Bridge Width	Same Width as Roadway	Same as Green Book	Same Width as Roadway	Same as Green Book
Vertical Clearance	16 ft	16.5 ft	16 ft	16.5 ft
Horizontal Clearance	Outside of clear zone as specified using roadside design guide	Same as Green Book	3 ft	Same as Green Book
Vertical Alignment	Meet Stopping Sight Distance Requirement	Length ≥ 1,000 ft Meet Stopping Sight Distance Requirement	Meet Stopping Sight Distance Requirement	Length ≥ 1,000 ft Meet Stopping Sight Distance Requirement

Table 3 Minimum design requirements for collectors

Criteria	Collectors			
	Rural		Urban	
	Green Book	UDOT	Green Book	UDOT
Design Speed	45-50 mph Not less than posted/proposed posted speed and as high as is reasonable	Same as Green Book	30 mph or higher Not less than posted/proposed posted speed and as high as is reasonable	Same as Green Book
Lane Width	12 ft	12 ft	12 ft	12 ft
Shoulder Width	4-8 ft	4-8 ft	4-8 ft	4-8 ft
Superelevation	As needed up to 8%	As needed up to 6%	As needed up to 6%	As needed up to 4%
Horizontal Alignment	Meet minimum for design speed	Same as Green Book	Meet minimum for design speed	Same as Green Book
Grade	5-12% Maximum 0.5% Minimum	5-12% Maximum 0.5% Minimum	6-14% Maximum 0.5% Minimum	6-14% Maximum 0.5% Minimum
Cross Slope	1.5-2%	2%	1.5-3%	2%
Stopping Sight Distance	Meet minimum for design speed	Same as Green Book	Meet minimum for design speed	Same as Green Book
Structural Capacity	H 15	HS 25 or HL 93	None	HS 25 or HL 93
Bridge Width	Same Width as Roadway	Same as Green Book	Same Width as Roadway	Same as Green Book
Vertical Clearance	14 ft	16.5 ft	14 ft	16.5 ft
Horizontal Clearance	10 ft	Same as Green Book	1.5 ft beyond face of curb	Same as Green Book
Vertical Alignment	Meet Stopping Sight Distance Requirement	Meet Stopping Sight Distance Requirement	Meet Stopping Sight Distance Requirement	Meet Stopping Sight Distance Requirement

Documentation on the selection and effectiveness of safety mitigation measures, sometimes implemented with a design exception, also varies *(7)*. Several design exception related research topics were identified, including *(7)*:

- Actual benefits – evaluate the benefits of preparing design exceptions;
- Tort liability – evaluate the magnitude of claims, plaintiff and defendant legal doctrines, awards and settlement amounts, and agency risk factors;
- Analytic techniques – develop practitioner guidance for evaluating the safety implications of design exceptions; and
- Mitigation – provide guidance on mitigation measures for various design criteria.

Tort liability is a legal issue for state DOTs that do not have sovereign immunity from being sued for civil wrong or injury to person or property due to negligence *(13)*. Negligence in design is often considered to have occurred when design standards are not met, the design is considered to be flawed, or the road segment in question is known to have had safety issues for which nothing has been done to correct the issues. In the case of design exceptions, jurors in a court will likely view the existence of a design exception as negligence on the part of the DOT unless it can be shown that the existence of a design exception does not, by virtue of its existence, mean that the road segment in question will be less safe than if the design standard was met.

The objective of this research is to compare safety, measured by expected crash frequency and severity, on road segments where design exceptions were approved and constructed to safety on similar road segments where no design exceptions were approved and constructed. The project will use data from the State of Utah. A study that looks at the safety effects of design exceptions in this way would have the following expected benefits that overlap each of the research needs identified above:

- Provide insights into the effectiveness of UDOT's current design exception preparation and approval process;
- Create additional documentation, as recommended and outlined by previous researchers that includes an evaluation of the designs resulting from the design exceptions *(13) (7)*; and
- Outline a methodology for other states to reference when conducting similar safety evaluations of design exceptions.

Literature Review

Safety Impacts of Design Exceptions

Little is known about the actual safety impacts of design exceptions. In one study, data were gathered for 562 design exceptions on 319 projects in Kentucky completed between 1993 and 2000 (average 1.8 design exceptions per project *(5)*). The majority of projects were bridge replacements (57%), followed by roadway widening (13%), and turning lane additions (9%). The data included exceptions to the 13 controlling criteria as well as to several supplemental criteria used in Kentucky (e.g., ditch width, number of lanes, access spacing, and guardrail end treatment). The most frequent exception was for using a design speed that was lower than the posted speed limit (34%), followed by exceptions to minimum sight distance (12%), minimum curve radius (12%), and shoulder width (11%).

A safety analysis was conducted using data from 86 of the 319 sites. Two types of study designs were used to investigate the safety effects of design exceptions: 1) naive before-after studies where safety 'after' the project with one or more design exceptions was compared to safety ‘before’ the project; and 2) a cross-sectional study where safety ‘after’ the project with one or more design exceptions was compared to the statewide ‘average safety’ for similar facility types.

A comparison of crash rates was the only analysis method used in both the before-after and cross-sectional studies. The conclusions indicated that the use of design exceptions in Kentucky did not result in a higher crash rate than the statewide average for similar facility types. The conclusions also indicated that projects constructed with design exceptions resulted in an improvement over the ‘before’ condition at those locations. The study design and the use of crash rates were the most significant analytical limitations of the study. The naive before-after method used assumes that nothing changed from ‘before’ to ‘after’ periods other than traffic volumes and the implementation of a design exception. The cross-sectional evaluation assumes nothing is different between locations with and without design exceptions other than traffic volume and the design exception. Finally, the use of crash rates can lead to incorrect conclusions about safety. Crash rates assume a linear relationship between traffic volumes and crashes. This is often not the case; additional detail can be found in *(14)*.

The impacts of design exceptions on both the frequency and severity of vehicle crashes were assessed using data from Indiana *(6)*. Data were collected at 48 locations with exceptions to “Level-One” design criteria (35 on bridges and 13 on road segments) and at 98 similar locations without design exceptions. Standard multinomial logit models and mixed multinomial logit models were used to analyze crash severity. Standard negative binomial models and a random parameter negative binomial model were used to analyze crash frequency. Five years of crash data were used for model estimation.

Parameter significance in the logit models, in addition to the results of a likelihood ratio test of models estimated at design-exception-sites and non-design-exception sites, suggested that design exceptions do not have a statistically significant impact on crash severity. Parameter significance for in the negative binomial models suggested that design exceptions do not have an effect on expected crash frequency. However, the likelihood ratio test of models estimated at design-exception-sites and non-design-exception-sites indicated a different crash generating process. The need for more data to explore this finding in greater detail was noted.

The results of the Indiana study indicated that the current design exception process in Indiana was adequate to avoid adverse safety impacts resulting from design exceptions. Model results showed that design exceptions granted in Indiana between 1998 and 2003 did not have a negative effect on safety. The authors recognized that the number of design exceptions used in their study was too small to make broad generalizations about design exception policy. The study served as a key reference to the study design and analysis approach described in this thesis.

There is a large body of research on the relationships between road geometric design and safety that have resulted in CMFs for geometric features. A review of these studies was conducted to determine what was known about the relationships between the 13 controlling criteria and safety. Four resources were used: the AASHTO *Highway Safety Manual* (8), *Roadway Safety Design Synthesis (15), Roadway Safety Design Workbook (16)*, and FHWA's *Crash Modification Factors Clearinghouse (17).* Findings of this review are summarized in Table 4. The table illustrates whether or not there are documented relationships between the 13 controlling criteria and crash frequency, crash

Table 4 Controlling criteria safety references

No.	Design Criteria	Safety Information				
		Rural			Urban	
		Freeways	Multilane highways	Two-lane highways	Freeways	Arterials
1	Design speed [a]	FR[1,2]; SV[2]	FR[1,4]	FR[1,4]; SV[1]	FR[1,2]; SV[1,2]	FR[1,4]
2	Horizontal alignment	FR[1]; FR[2]	FR[1,2]; SV[2]	FR[1,2,3]; SV[2]	FR[1,2]	FR[2];SV[2]
3	Superelevation		FR[1]	FR[1,2,3]; SV[2]		
4	Grade	FR[1,2]; SV[2]	FR[1,2]; SV[2]	FR[1,2,3]; SV[2]	FR[1,2]; SV[2]	FR[1]
5	Vertical clearance					
6	Vertical alignment	FR[4]; SV[4]	FR[4]; SV[4]	FR[4]; SV[4]	FR[4]; SV[4]	FR[4]; SV[4]
7	Stopping sight distance					
8	Travel lane width	FR[1,2], SV[1,2]; TY[1]	FR[1,2,3]; TY[1,3]; SV[2]	FR[1,2,3]; TY[1,3]; SV[1,2]	FR[1,2,3], TY[1]; SV[2,3]	FR[2,3]; SV[2]
9	Cross slope					
10	Shoulder width	FR[1,2,4]; SV[1,2]; TY[1]	FR[1,2,3,4]; TY[1,3]; SV[2]	FR[1,2,3,4]; SV[1,2]; TY[1,3];	FR[1,2,4]; SV[1,2]; TY[1]	FR[2,4]; SV[2]
11	Horizontal clearance to obstructions	FR[1,2,3]; TY[1]; SV[2]	FR[1,2]; TY[1]; SV[2]	FR[1,2,3];TY[1]; SV[2]	FR[1,2]; TY[1]; SV[2]	FR[2,3]; SV[2]; TY[3]
12	Bridge width	FR[4]	FR[1,4]; TY[1]	FR[1,4]; TY[1]	FR[4]	FR[4]
13	Structural capacity					

[a] Posted speed is used as a surrogate for design speed in the cited models. Actual operating speeds likely differ from both design speed and posted speed.
FR[i, j, k] = documented effect between design criteria and crash frequency in references i, j, and k
SV[i, j, k] = documented effect between design criteria and crash severity in references i, j, and k
TY[i, j, k] = documented effect between design criteria and crash type in references i, j, and k
References: 1 = *Road Safety Design Synthesis (15)*; 2 = *Road Safety Design Workbook (16)*; 3 = *Highway Safety Manual (8)*; 4 = CMF Clearinghouse *(17)*

severity, and crash type. Findings are disaggregated by area type and facility type. Some researchers have suggested that results of studies such as those behind Table 4, with corresponding CMFs, can be used to assess the safety effects of design exceptions *(18)*. However, the studies leading to these CMFs tend to use data from a broad sample of road segments that may or may not have design exceptions and that are intended to be a randomly selected sample of the road segment population. Estimating the safety effects of design exceptions from these models may be misleading, as locations with design exceptions are likely to have systematic differences from locations without design exceptions. In other words, "roadway segments that are granted design exceptions are likely to be a non-random sample of the roadway segment population…" *(6).* The work in this thesis addresses this limitation by directly estimating the difference between the safety of a location with one or more design exceptions and the predicted safety of that same location without a design exception.

Research Design Methods

Observational Studies

Observational studies (also called quasi-experiments) are experimental studies that compare groups, but lack random assignment into the groups *(19)*. The purpose of observational studies can be defined by the following *(20)*:

> Quasi-experiments share with all other experiments a similar purpose to test descriptive causal hypothesis about manipulable causes... But, by definition, quasi-experiments lack random assignment. Assignment to conditions is by means of self-selection, by which units choose treatment for themselves, or means of administrator selection, by which teachers, bureaucrats, legislators, therapists, physicians, or others decide which persons should get treatment.

In other words, observational studies are studies that use observed (non-experimental) data. The reasons for using nonexperimental data usually come from ethical issues. In order for an experiment involving humans to be ethical and feasible (allowing experimentation), there are a number of requirements must be met *(21)*:

> Experiments with human subjects are often ethical and feasible when (a) all of the competing treatments under study are either harmless or intended and expected to benefit the recipients, (b) the best treatment is not known, and in light of this, subjects consent to be randomized, and (c) the investigator can control the assignment and delivery of treatments... When experiments are not ethical or feasible, the effects of treatments are examined in an observational study.

In the case of this study, roads with and without design exceptions are not randomly selected. Locations with design exceptions are likely to have systematic differences from locations without design exceptions. Systematic differences in the data could include differences in the characteristics of the road segments (e.g., the number of horizontal curves per mile, etc.) and other differences between the locations with and without design exceptions. These systematic differences can be classified as selection bias. Selection bias leads to issues in the study design and methods used. These issues are discussed in the 'Propensity Score' section below.

The design of observational studies can take different forms, are based on different assumptions, and have different limitations. The different forms include the naive before-after study, before-after with comparison group, before-after with comparison group and empirical bayes, cross-sectional, and longitudinal studies. With these different types of observational studies, all of them attempt to answer the question of 'what would have been' if the treatment (in this case, design exception) had not been implemented and compare what 'would have been' with the actual outcome where the treatment was implemented.

<u>Naive Before-After</u>

The naive before-after study is the simplest of the different types of observational studies. In transportation safety research, this method consists of comparing the before-period crashes to the after period crashes *(14)*. The idea is that the before-period crashes are the same as what the after period would have been if the treatment had not been implemented. Thus, the outcome in the before-period is used to predict what the outcome would have been in the after period if the treatment had not been implemented. This method is called naive because of the assumption being made that nothing changed from the before-period to the after-period other than the treatment. However, five factors that make this assumption questionable *(14)*:

1. Traffic, weather, vehicle, and user characteristics change over time. These factors may affect the change in crashes in addition to the treatment.
2. Other unaccounted for treatments and programs that are not of interest may have been applied during the observed period on a portion of or the entire observational group.
3. The count of Property Damage Only (PDO) crashes is affected by the cost of repairs and reporting requirements that change over time.
4. The probability of reportable crashes being reported may change over time.
5. The entities may have been chosen for the treatment due to either unusually high or unusually low crash counts in the past. If this is the case, the unusual crash history is unlikely to be a good basis for predicting what would be expected in the future had the treatment not been applied.

Due to these factors, this method can serve as a starting point, but has many limitations when inferences of the effects of a treatment are sought. Thus, other methods that do not have the same restricting assumption are preferred to the naive before-after study.

Before-After with Adjustments in Measured Factors and Before-After with Comparison Group

The before-after study with adjustments in measured factors is similar to the naive before-after study, but it accounts for changes in traffic volume and other measureable factors. These measureable factors are accounted for in this method by explicitly modeling them. The limitation here is that all of the factors accounted for must be measured and understood *(14)*. The implications of this method are that the inferences made by explicitly modeling factors related to the outcome are that the modeled factors can be the only factors that influence the outcome (i.e., crash frequency). Otherwise, the estimated effects can lead to incorrect inferences.

In order to account for factors that are not measured, not recognized, or that are not understood, a comparison group can be used. A comparison group is a group made of observations (e.g., road segments) that have similar attributes as the treatment group (e.g., road segments with design exceptions) but did not receive the treatment. It is assumed that the comparison group can be used to predict ‘what would have been’ in the after period for the treatment group by comparing the outcomes of the treatment and comparison groups in both the before period and after period. It has been noted that a comparison group should only be used to account for factors that are not measured, not recognized, or that are not understood. The factors that are known, measured, and understood should be explicitly modeled using regression techniques *(14)*.

Before-After with Reference Group and Empirical Bayes

This method is similar to the before-after with comparison group method. When empirical Bayesian analysis is used, the comparison group is called a reference group. The difference between this method and the before-after with comparison group method is that crash trends are accounted for by the application of a reference group and empirical Bayesian analysis. This method can deal with regression-to-the-mean issues and yields more precise estimates for treatment effects *(14)*. Regression-to-the-mean is a phenomenon that occurs when a road entity has either higher or lower crash counts than expected and over time converges on the mean. The reasons for the higher or lower crash counts is random and not related to the treatment, but other analysis methods would assume that the change (higher or lower counts) caused by regression-to-the-mean was actually a result of the treatment. The method can also count for changes in factors measured and understood and changes in factors not measured and not understood through the application of a safety performance function estimated using the reference group.

Cross-Sectional

In a before-after study, there is a change from the ‘before’ to ‘after’ periods. In a cross-sectional study, there is no such change *(22)*. A cross-sectional study is a research method used to analyze data that is taken at a single point in time. The single point in time can refer to a period of time, such as a year or a sum of years. This method also uses a comparison group, but the assumption made is different. The assumption made about the comparison group for a cross-sectional study is that the outcome of the comparison group is a good representation of ‘what would have been’ for the treatment group if the treatment had not been implemented. The implication is that the comparison group can be used to compare the outcomes between the two groups using regression to estimate the effects of the treatment. The effects of characteristics (e.g., number of lanes, presence of intersections, or operating speed) are explicitly accounted for in cross-sectional studies by combining the treatment and comparison groups and using regression analysis. The effects of the treatment can be estimated via use of an indicator variable in the regression models. One benefit of this method is that it is not subject to regression-to-the-mean bias *(23)*. However, this method is often subject to issues such as measurement error, selection bias, and omitted variable bias. Measurement error and omitted variable bias are discussed below. Selection bias is discussed in more detail in the discussion of propensity scores.

Measurement error is simply error in the measurements of variable observations. This occurs in both experimental and observational data. Measurement error in either the dependent variable or in any of the independent variables often results in a non-normally distributed and inflated error term for the model *(24)*. This effect results in the variance of the model being inflated. This also has deleterious effects on goodness-of-fit criteria (such as F-ratio and R-squared estimates) and parameter estimate standard errors due to the non-normally distributed error terms and inflated variance. Measurement error in the independent variables also leads to biased coefficient estimates *(24)*.

Omitted variable bias occurs when significant explanatory variables are omitted from the model. When this happens, the parameter estimates in the model will be biased and can lead to incorrect inferences *(25)*. The parameter estimates are biased for parameters that are correlated with the omitted variable and unbiased if the parameter is not correlated with the omitted variable *(24)*. In both cases where omitted variables are correlated and uncorrelated with variables included in the model, the usual confidence interval and hypothesis testing procedures are unreliable *(24)*. In other words, omitted variable bias can cause parameter estimation error and error in the estimation of model fit. It has been suggested that, if practical, all logical variables should be included in models in order to minimize the probability of omitted variable bias in models *(26)*. Thus, for all of the modeling in this project, all observed relevant variables were included in the model specifications. For indicator variables, each 'value' must have been observed on at least 10% of the road segments to be included. All other logical variables that were collected were also included.

Longitudinal Studies

Longitudinal data (panel data) are cross-sectional observations over repeated units of time. Longitudinal models are models that consider both the cross-sectional and time series characteristics of data. These models can account for cross-sectional heterogeneity in the data *(27)*. Longitudinal models have the ability to deal with omitted variable bias, address multicollinearity issues, and allow for analysis of dynamic behavior of the observations over time *(26)*. However, longitudinal models have restrictions. One of the main restrictions is that fixed effects longitudinal models cannot estimate the effects of variables that do not vary over time. For estimates of the effects of time-invariant predictor variables, the use of random effects longitudinal models is needed.

Why Cross-Sectional Design Used in This Study

The data used for this study were taken from observed data. The design exception locations where found using design exception application forms. Information on the presence of design exceptions on the locations indicated in the design exception application forms prior to the construction of the current projects was not available. Crash data earlier than 2006 were also unavailable. Locations with design exceptions were also experiencing other changes as part of the construction projects in addition to the design exception. Thus, it was not possible to use a before-after study design. A longitudinal study design also did not make sense as the data used were over a short time period and the variable of interest (presence of one or more design exceptions) did not change over time. For these reasons, a cross-sectional design was used for this study.

Propensity Scores

In observational studies, ‘treated locations’ (i.e., locations with design exceptions in this case) and ‘untreated locations’ (i.e., locations without design exceptions) are not determined at random like they are in experimental studies. This characteristic of observational studies may introduce ‘selection bias’ into model parameter estimates due to initial differences in the characteristics between units that receive a treatment and units that do not. Selection bias occurs when the units selected for treatment and comparison are not selected at random. Sources of selection bias include self-selection, researcher selection, administrative selection, geographic selection, measurement selection, and attrition selection *(19)*. In transportation research, selection bias often comes in the form of either researcher selection or administrative selection. These come in the form where the treatment was given due to certain observed characteristics of a site or group. Selection of a treatment group and a control (comparison) group based on certain characteristics (not random selection) leads to initial differences in the groups. These differences are classified as either overt bias or hidden bias. Overt bias is bias (differences) in the data that can be observed. Hidden bias is differences between the treatment and comparison groups that are unmeasured. Potential strategies to 'adjust' for selection bias have been proposed and include propensity score analysis [see, for example, the discussion in *(21)*].

Propensity score analysis is a class of statistical methods that are used to reduce selection bias in observational studies. Propensity score analysis is used in observational studies conducted in the fields of epidemiology, medicine, economics, financing, education, and the social sciences *(19)*. A propensity score is the statistical probability that an observation did or did not receive a treatment. The idea behind propensity score analysis is to mimic 'covariate balance' achieved by randomization in experimental studies. It has been suggested that the use of propensity score analysis could reduce selection bias in observational study results by as much as 95% *(28)*.

Propensity scores are used to detect differences in the sites with and without a treatment and are used to balance the data in such a way that both overt bias and hidden bias are minimized. Often, these detected differences in the data are not the result of the treatment itself *(21)*. In the case of this study, any detected differences in the estimates of safety on road segments with and without design exceptions could be a result of 'other' differences in the characteristics of the road segments that are unrelated to the design exceptions (i.e., selection bias). This could then lead to incorrect conclusions about the safety impacts of design exceptions.

Matching treatment and comparison sites based on the propensity scores plus one or two other key covariates has a tendency to balance all other covariates, including unobserved covariates *(21)*. Under the assumption that unobserved variables have the same effects on crash outcomes for the treatment and comparison groups, this balance of unobserved covariates reduces omitted variable bias *(29)*. Thus, selection bias and omitted variable bias are both reduced in observational studies via proper application of propensity score analysis.

RESEARCH METHODS

Design Exception Effects on Expected Crash Frequency

The relationship between design exception presence and crash frequency was explored in this study using a negative binomial regression modeling approach. The use of Poisson regression to model the relationships between crash frequency, traffic volumes, and weather conditions was introduced by *(30)*. Negative binomial regression, a more general form of Poisson regression, was later used to explore the relationship between crash frequencies, daily traffic, and highway geometric design variables *(31)*. In the negative binomial model, the expected number of crashes of type *i* on segment *j* is expressed as:

$$\mu_{ij} = E(Y_{ij}) = \exp(X_j\beta + \ln L_j) \quad \text{(Eq. 1)}$$

where:

$\mu_{ij} = E(Y_{ij})$ = the expected number of crashes of type *i* on segment *j*;

X_j = a set of traffic and geometric variables characterizing segment *j*;

β= regression coefficients estimated with maximum likelihood that quantify the relationship between $E(Y_{ij})$ and variables in X;

L_j = length of segment *j*; and,

$\ln L_j$ = the natural logarithm of segment length.

The mean-variance relationship of the negative binomial regression model is expressed as:

$$VAR(Y_{ij}) = E(Y_{ij}) + \alpha[E(Y_{ij})]^2 \qquad \text{(Eq. 2)}$$

where:

$E(Y_{ij})$ = the expected number of crashes of type *i* on segment *j*;

$VAR(Y_{ij})$ = variance of of crashes of type *i* on segment *j*; and

α = overdispersion parameter.

The data are over-dispersed if α is greater than zero and under-dispersed if α is less than zero. The negative binomial model reduces to the Poisson model if α equals zero.

The presence of one or more design exceptions, coded as an indicator variable (1 = one or more design exceptions; 0 = no design exceptions), was the primary variable of interest in the matrix of explanatory variables, X_j. However, a number of other traffic and geometric variables were included in model specifications to decrease unexplained variation in expected crash frequency and to try and minimize omitted variable bias. Omitted variable bias would result in the model over- or under- estimating the safety effects of design exceptions due to other variables that influence crash frequency and are correlated with design exception presence, but are excluded from the model.

Segment length, L, was included in the models as an offset variable (i.e., the regression coefficient for the natural logarithm of segment length was constrained to 1.0), and captures the linear increase in expected crash frequency with an increase in segment length due to increased exposure. Model fit was evaluated using the McFadden Pseudo

R-Squared. The McFadden Pseudo R-Squared (ρ^2) is analogous to the R-squared value used to express the goodness of fit of a standard, ordinary least squares regression model. It is expressed as:

$$\rho^2 = 1 - \frac{L(full)}{L(0)} \qquad \text{(Eq. 3)}$$

where:

ρ^2 = McFadden Pseudo R-Squared;

L(*full*) = log-likelihood of the model with explanatory variables; and,

L(0) = log-likelihood of the intercept-only model.

The McFadden Pseudo R-Squared may take a value between 0 and 1; the value moves closer to 1 as model fit improves. Negative binomial regression models were estimated separately for 'total' crashes (all types and severities), fatal-plus-injury crashes (the crash resulted in at least one injury or fatality), and property damage only crashes (the crash did not result in any injuries).

The safety effects of design exceptions were also checked using a transferability test. This test checks to see if parameters are transferable from one set of data to another (i.e., model parameters are transferable from the design exception road data to the road data without design exceptions). This approach was also used in the design exception research done in Indiana *(6)*. It is a likelihood ratio test for transferability of estimated model parameters *(24)*, specified as:

$$X^2 = -2[\mathrm{LL(Full)} - \mathrm{LL(DE)} - \mathrm{LL(NDE)}] \qquad \text{(Eq. 4)}$$

where:

LL(full) is log-likelihood from a model including the segments with design exceptions and comparison segments;

LL(DE) is the log-likelihood from a design exception only model; and

LL(NDE) is the log-likelihood from a comparison segment only model.

The test statistic X^2 is X^2-distributed with degrees of freedom equal to the sum of the number of parameters of the design exception only and comparison group only models minus the number of parameters in the full model. The result of this test is a X^2 statistic that provides the confidence level that the null hypothesis (no difference between design exception only and comparison group only models) can be rejected. It should be noted that the models must be well specified as omitted variables and other specification errors may lead to erroneously rejecting transferability *(24)*.

The two different methods, regression using an indicator variable and the transferability test, are different methods and are based on different assumptions. With the indicator variable approach, an assumption is made that all of the other independent variables have the same effect on the outcome (in this case, crash frequency). What this means is that the parameter estimates are simply the mean effect of the independent variables on the outcome for all locations, whether in the treatment group or comparison group. The transferability test relaxes this assumption. However, the transferability model makes two important assumptions. The first assumption is that, for the model to be transferable, the treatment did not affect the outcome. The second assumption is that all of the independent variables modeled, statistically speaking, have the same effect on the outcome for both the model using only the treatment group (locations with design exceptions) and the model using only the comparison group (locations without design exceptions). If either of these is not the case, or the models are not well specified, the models will not be transferable. Conversely, if the models are transferable it can be concluded that the treatment had no effect on the outcome, all of the independent variables included in the model have the same effect on the outcome, and the models are well specified.

Design Exception Effects on Expected Crash Severity

The relationship between design exception presence and crash severity was explored in three ways: 1) computing severity distributions at locations with and without design exceptions, 2) estimating separate negative binomial regression models by severity level, and 3) estimating multinomial logit models. The first two approaches are currently used in the predictive methods of the *Highway Safety Manual (8)*. 'Default' severity distributions (i.e., alternative method 1 above) are applied to the total crash prediction in Chapter 10 of the *Highway Safety Manual* (rural, two-lane). Chapter 11 of the *Highway Safety Manual* (rural, multilane) includes separate regression equations to independently predict the average crash frequency for total (KABCO) crashes, fatal-plus-injury (KABC) crashes, and fatal-plus-injury-without-possible-injury (KAB) crashes (i.e., alternative method 2 above). The *Highway Safety Manual*, Chapter 11 method itself does not predict PDO crashes.

The predictive method in Chapter 12 of the *Highway Safety Manual* (urban/suburban) requires that three SPFs be applied independently to predict average crash frequencies for total (KABCO), fatal-plus-injury (KABC), and property damage only (O) crashes. The sum of fatal-plus-injury crashes and property damage only crashes do not add up to equal the total crashes since the SPFs were independently estimated, so the following adjustments are made to the fatal-plus-injury and property damage only predictions:

$$KABC(new) = KABCO\left(\frac{KABC}{KABC+O}\right) \quad \text{(Eq. 5)}$$

$$O(new) = KABCO - KABC(new) \quad \text{(Eq. 6)}$$

Modeling crash severity is important to understanding the safety effects of design exceptions. Severity distributions may change significantly with traffic volume. Design decisions may also influence severity distributions, through a resulting increase or decrease in operating speeds (e.g., an increase or decrease in lane and shoulder widths). Severity distributions are likely to vary differently with traffic volumes and design decisions. Computing 'default' severity distributions with and without design exceptions may not capture these complexities. Estimating separate negative binomial regression models by severity level may also have limitations. A series of crash frequency models, developed for each level of severity, "can introduce significant estimation errors in that it implicitly assumes that the factors generating the occurrence of an accident are independent across severity outcomes." *(32)*

Estimating a "severity distribution function" using logit models is one possible alternative to address these issues. The logit models produce the probabilities (or proportions) of crash severity outcomes as a function of traffic volume, geometry, and other road characteristics, including the presence of one or more design exceptions. The multinomial logit *(33)*, nested logit *(34)*, and ordered outcome models *(35)* are possible model alternatives. The databases used to estimate the severity models consist of the same crashes and road segments as the frequency model databases, but are restructured so that the basic observation unit (i.e., database row) is the crash instead of the road segment. A body of published research exists on the application of discrete choice models to explore crash severity *(36)*, but their application in applied safety research and in practice (e.g., the *Highway Safety Manual*) is relatively limited.

The multinomial logit model is a widely used discrete choice model. It was used as the third alternative in this research to model crash severity, resulting in a severity distribution function. The presence of one or more design exceptions was again coded as an indicator variable (1 = one or more design exceptions; 0 = no design exceptions) in the utility function for each severity category. This alternative addressed the limitations of the frequency-based approaches identified in the preceding discussion. In the multinomial logit model, the probability that accident n will have severity i [$p_n(i)$] is given by

$$p_n(i) = \exp(\beta_i X_n) / \sum_I \exp(\beta_I X_n) \qquad \text{(Eq. 7)}$$

where X_n is a vector of variables that will determine the crash severity and, β_i is a vector of parameters to be estimated. Utility functions are defined for the severity likelihoods as

$$S_{in} = \beta_i X_n + \varepsilon_{in} \qquad \text{(Eq. 8)}$$

where ε_{in} is a set of error terms that account for unobserved variables. The error terms for each choice should follow independent extreme value distributions (also called Gumbel or type I extreme value). The key assumption is that the errors are independent of each other (also called the independence of irrelevant alternatives or IIA assumption). This independence means that the unobserved portion of utility for one severity alternative is unrelated to the unobserved portion of utility for another severity alternative. The IIA assumption can be tested using a hausman test *(37)*. For the hausman test, if the p-value ≤ 0.05, then the IIA assumption is likely violated. If the unobserved portion of utility is correlated over alternatives (IIA assumption is violated), then there are three options: 1) use a different model that allows for correlated errors, such as nested logit or mixed logit model, 2) respecify the representative utility so that the source of the correlation is captured explicitly and thus the remaining errors are independent, or 3) use the logit model under the current specification of representative utility, considering the model to be an approximation.

The McFadden pseudo r-squared, as defines in the previous section, is also used to assess the goodness of fit of the multinomial logit model.

Propensity Scores

There are several different propensity score analysis methods, each of which are based on different assumptions and that have different advantages and limitations depending on the study designs employed. For a full discussion of the different methods, their assumptions, limitations, and applications see *(19)*.

Five steps have been identified that can be used in the propensity score analysis Process *(38)*. The steps are as follows:

1. Estimate Propensity Scores
2. Select a Matching Algorithm
3. Check Overlap/Common Support
4. Estimate Matching Quality/Effect
5. Conduct Sensitivity Analysis

These steps provide an overview of the considerations that should be included in propensity score analysis. For the purposes of this thesis, a more simplistic version of this process was used as described by *(39)* and provided below:

1. Start with a logit (or probit) model to estimate the score. Only include variables that are not used to decide what units receive treatment or that are not affected by the decision of the treatment (e.g., traffic volumes, number of through lanes, etc.).
2. Sort the data according to estimated propensity score (ranking from lowest to highest).
3. Stratify all observations such that propensity scores within stratum for treated and comparison units are close (no significant difference in the means). It has been suggested that five strata are enough to remove as much as 95% of the bias *(28)*.
4. Conduct a statistical test to determine if, for all covariates, differences in means across treated and comparison units within each stratum are not significantly different than zero. It has been suggested that matching on the propensity score plus one or two other key covariates tends to balance all other covariates including unobserved covariates *(21)*. If there are no unobserved covariates to balance, then balancing on only the propensity score is sufficient *(21).* Thus, it is

not necessary to check the balance of all covariates. Thus, the statistical test can be implemented via the following *(39)*:

a. If selected covariates are balanced between treated and comparison observations for all strata, stop.

b. If selected covariates are not balanced for some stratum, divide the stratum into finer strata and reevaluate.

c. If a selected covariate is not balanced for many strata, modify the logit by adding interaction terms and/or higher-order terms of the covariate and reevaluate.

Step one is the estimation technique used for this project (using a binomial logit or probit). The binomial logit was selected for this thesis as the probit makes the assumption that all of the unobserved components of utility are normally distributed, which is not likely the case for the data used *(40)*. Steps 2 and 3 are the matching algorithm. Step 4 estimates the matching quality and sensitivity for the propensity scores. This method assumes that there is no measurement error in the data. For all propensity score analysis methods that can be used in cross-sectional studies, this same assumption must be made *(19)*. There is, however, a method that can deal with both measurement error and selection bias that can be used in before-after studies with comparison groups. This method is known as a difference-in-differences propensity score analysis with nonparametric regression *(19)*. As this is not used in this study, it will not be discussed further. Those interested in this method can read more in *(19) (41)*.

The binary logit is similar to the multinomial logit, but with two possible outcomes. It is specified as:

$$p_n(i) = \exp(\beta_i X_n) / (1 + \exp(\beta_i X_n))$$

(Eq. 9)

where X_n is the set of variables from step 1 of the propensity score algorithm, β_i is a vector of parameters to be estimated and, $p_n(i)$ is the probability that a road segment received the treatment (design exception). The utility function is defined for the outcome as

$$S_{in} = \beta_i X_n + \varepsilon_{in} \quad \text{(Eq. 10)}$$

where ε_{in} is a set of error terms that account for unobserved variables. As in the multinomial logit, the error terms for each choice should follow independent extreme value distributions (also called Gumbel or type I extreme value).

Step 4 of the algorithm is essential to the propensity score analysis. It checks covariate balance which is what the method seeks to achieve. It is not enough to simply calculate the propensity score and balance the data based on the probability of receiving the treatment unless it is known that there are no unobserved covariates to balance. As this is never known for observational studies, researchers using this method for propensity score analysis should always balance the data on the propensity score plus one or two other key variables.

DATA COLLECTION

Data Sources and Collection

Data were collected for design exceptions granted by UDOT in the years 2001 through 2006. Design exception request and approval forms were obtained from UDOT. Project numbers, PIN numbers, approval dates, routes, project locations (e.g., start and end mile post for the project), pavement types, pavement widths, right-of-way widths, clear zone distances, design exception elements, and mitigation information were obtained for each of the design exception locations from the forms.

UDOT assisted the research team with updating the mileposts on the design exception and approval forms to be consistent with milepost referencing in the crash data used for this project. UDOT also converted other location descriptions (e.g., a qualitative description of an intersection) to mileposts in the cases where milepost numbers were not directly used to define project boundaries. UDOT's PDBS was used to find the start and end mileposts for the project as recorded by the RE on the project. If no milepost data were recorded in PDBS, a Business Analyst was contacted to help locate the originally advertised project plans. The coversheet of the advertised project plan showed the start and end milepost for each project. Milepost data were then taken to the Crash Studies Supervisor to validate that the milepost recorded by the RE at the time the project was constructed was consistent with milepost referencing in the crash data used for this project. As a final check, the project locations and mileposts were checked in Google

Earth to make sure that they made sense by comparing them with the location descriptions in the project files. PDBS was used to find the date the project was "substantially complete." In the event that no substantially complete date was available, the "final acceptance date" was provided. In all cases, the project was completed prior to the data analysis years. PDBS was also used to verify the Project and Pin Numbers collected from the original design exception data. If a Project or Pin was invalid, PDBS was used to locate the valid or updated number. In the event a valid number could not be located, it was concluded that the project was never constructed.

Other data were collected using Google Earth, Google Street View, UDOT functional classification maps, and UDOT Traffic Data. These data included information on area type (i.e., urban or rural), number of horizontal curves within the project boundaries, number of through lanes, presence and type of auxiliary lanes, and the number of intersections or interchanges within the project boundaries. Functional classification and daily traffic volumes for the years 2007 through 2010 were also obtained. A full description of all variables that were collected, coded, and considered for the model specifications are shown in Table 5.

Data for a total of 63 projects (48 on road segments, four on bridges, eight at intersections, and three at interchanges) that were built with design exceptions between 2001 and 2006 were collected. Due to the small samples of bridge, intersection, and interchange projects, only data collected for the road segment projects were used in this study. Design exceptions for structural capacity or bridge width were not explored. Two design exceptions for vertical clearance were included in the data. Crashes on the roadway passing underneath the bridge were modeled. The distribution of design

Table 5 Variable descriptions

Variable Notation	Variable Description
No.	Site number
Pin	Project PIN (assigned by UDOT)
Route	Route number
Start_MP	Beginning milepost of segment
End_MP	Ending milepost of segment
Type	Site type: segment, bridge, intersection, or interchange (only road segments used for this study)
Length	Segment length (miles)
LN_LEN	Natural logarithm of length
AVE_AADT	The Average of Annual Average Daily Traffic for the years 2007-2008 for aggregate models, 2007-2010 for nonfreeway models
LN_AADT	Natural logarithm of AVE_AADT
DE	Indicator variable for design exception presence (1 = one or more approved and constructed design exceptions on segment; 0 = no design exceptions on segment)
Non_FW	Indicator variable for facility type (1 = nonfreeway segment, 0 = freeway segment)
TOT_KABCO	Total crashes on road segment in years 2007-2008 (all types and severities)
TOT_KABC	Crashes on road segment in years 2007-2008 in at least one fatality or injury
TOT_K	Crashes on road segment in years 2007-2008 resulting in at least one fatality
TOT_O	Crashes on road segment in years 2007-2008 resulting in property damage only (i.e., no injuries)
Thru_Lanes	Total number of through lanes
TWO_TL	Indicator variable for number of through lanes (1 = segment has two through lanes; 0 = otherwise)
FOUR_TL	Indicator variable for number of through lanes (1 = segment has four through lanes; 0 = otherwise)
SIX_TL	Indicator variable for number of through lanes (1 = segment has six through lanes; 0 = otherwise)
EIGHT_TL	Indicator variable for number of through lanes (1 = segment has eight through lanes; 0 = otherwise)
NINE_TL	Indicator variable for number of through lanes (1 = segment has nine through lanes; 0 = otherwise)
TEN_TL	Indicator variable for number of through lanes (1 = segment has ten through lanes; 0 = otherwise)
SIX_TEN_TL	Indicator variable for number of through lanes (1 = segment has six, eight, or ten through lanes; 0 = otherwise)
EIGHT_TEN_TL	Indicator variable for number of through lanes (1 = segment has eight or ten through lanes; 0 = otherwise)
Aux_Lanes	Presence of auxiliary lanes (not including 2WLT)

Table 5 Variable descriptions (continued)

Divided	Indicator variable for median presence (1 = segment is divided, 0 = segment is undivided) that is not 2WLT or Trav_Divided
Trav_Divided	Indicator variable for median type (1 = segment has a traversable median that is not a two- way left turn lane; 0 = otherwise)
2WLT	Indicator variable for presence of two-way-left-turn-lane (1 = segment has two-way-left-turn-lane; 0 = otherwise)
HC	Number of horizontal curves on segment
HC_MILE	Number of horizontal curves per mile on segment
Rural	Indicator variable for area type, defined by the location urban boundaries (1 = rural; 0 = urban)
Non_FW_INTS	Number of at-grade intersections on nonfreeway segment (Non-FW_INTS = 0 if segment is a freeway)
FW_INTC	Number of interchanges on freeway segment (FW_INTC = 0 if segment is not a freeway)
Non_FW_INTS_M	Number of at-grade intersections per mile on nonfreeway segment (Non_FW_INTS_M = 0 if segment is a freeway)
FW_INTC_M	Number of interchanges per mile on freeway segment (FW_INTC_M = 0 if segment is not a freeway)
MPH_40_45	1 = Posted speed limit is either 40 or 45 mph, 0 = Otherwise
MPH_50_55	1 = Posted speed limit is either 50 or 55 mph, 0 = Otherwise
MPH_60_65	1 = Posted speed limit is either 60 or 65 mph, 0 = Otherwise
MPH_70_80	1 = Posted speed limit is either 70, 75, or 80 mph, 0 = Otherwise
Single_Truck_Ave	The percentage of traffic that is single trailer large trucks
Combo_Truck_Ave	The percentage of traffic that is multiple trailer large trucks
Trucks_Ave_Total	The percentage of traffic that is large trucks
DE_AADT	Interaction variable between design exceptions (DE) and traffic volume (AADT)
DE_Trucks_Total	Interaction variable between design exceptions (DE) and percentage of traffic volume that is large trucks (Trucks_Ave_Total)
Posted_Speed_Limit	The posted speed limit for the road segment in mph

exceptions across the 48 road segment projects used in this study is shown in Table 6. There was an average of 1.77 design exceptions per road segment project with a maximum of five design exceptions and minimum of one design exception.

Google Earth, Google Street View, UDOT functional classification maps, and UDOT traffic volume data were also used to identify and define road segments without design exceptions. These road segments made up the comparison group. The comparison group was carefully built to include locations that were similar to the locations with design exceptions (i.e., the treatment group). The exact location(s) of the design exception(s) within the project boundaries was determined, when possible. In these cases, segments with design exceptions were defined as beginning one-half mile ‘before’ the location of the exception and ending one-half mile ‘after’ the exception. The comparison segments were then also defined, when possible, within the project boundaries at locations without any design exceptions. This was done to maximize similarity between the treatment and comparison segments and ensure that the comparison locations did not have design exceptions on them (otherwise, they would be identified in the project documents). When this approach was not possible, the entire project was defined as the design exception segment. Locations along the same route and in near proximity to the project segment were then searched for possible comparison segments. Other areas were searched for similar road segments without design exceptions as a second alternative when additional sites were needed.

For each treatment location, at least two comparison locations with the same area type classification, functional classification, number of through lanes, number and type of auxiliary lanes, and similar traffic volumes were defined (except for urban freeway

Table 6 Design exception frequencies by facility type

Exception Type	Freeway		Nonfreeway		Total	
	Count	%	Count	%	Count	%
Design Speed	0	0.00%	3	4.92%	3	3.49%
Lane Width	2	8.00%	5	8.20%	7	8.14%
Shoulder Width	6	24.00%	18	29.51%	24	27.91%
Bridge Width	0	0.00%	0	0.00%	0	0.00%
Horizontal Alignment	2	8.00%	6	9.84%	8	9.30%
Superelevation	6	24.00%	1	1.64%	7	8.14%
Vertical Alignment	3	12.00%	6	9.84%	9	10.47%
Grade	1	4.00%	5	8.20%	6	6.98%
Stopping Sight Distance	3	12.00%	4	6.56%	7	8.14%
Cross Slope	1	4.00%	5	8.20%	6	6.98%
Vertical Clearance	1	4.00%	1	1.64%	2	2.33%
Lateral Offset to Obstruction	0	0.00%	7	11.48%	7	8.14%
Structural Capacity	0	0.00%	0	0.00%	0	0.00%
Total	25	100.00%	61	100.00%	86	100.00%

segments as noted in the following discussion). Data on any remaining variables that were defined for the treatment sites were then collected using Google Earth and Google Street View, including number of horizontal curves within the project boundaries, number of through lanes, presence and type of auxiliary lanes, and the number of intersections or interchanges within the segment boundaries.

Initially, 91 comparison segments were defined: two comparison locations for most design exception locations (two comparison locations were not available for urban freeway projects). Propensity scores were then used to assess the adequacy of the comparison site selection process. The propensity score analysis resulted in the research team defining 43 more comparison locations in an attempt to have a group of comparison segments with propensity scores comparable to the group of road segments with design exceptions. A final logistic regression was performed and final propensity scores were calculated and analyzed. Ultimately, a total of 132 comparison segments were used for modeling. The descriptive statistics for the aggregate, nonfreeway, and freeway data are shown in Table 7, Table 8, and Table 9, respectively. A map showing the locations of the design exception segments and comparison segments is shown in Figure 1.

Crash Data

Crash data from the years 2007 through 2010 were obtained from UDOT and used for the analysis. Crash, vehicle, and occupant files were provided. Crash location, defined by route and milepost, and crash severity were the primary variables of interest for this study. Crash severity was defined as the most severe injury sustained by any occupant involved the crash on the KABCO scale, where K = fatality, A = incapacitating injury, B = nonincapacitating injury, C = possible injury, and O = no injury (i.e., property damage only). Variable definitions and descriptive statistics related to the crash data are provided in Table 5 and Table 7 through Table 9.

The total numbers of crashes available for the aggregate model estimation were:

- 44,714 crashes for the crash frequency models for all types and severities (KABCO) and the severity models of the KABCO crashes;
- 11,230 crashes for the fatal-plus-injury crash frequency models (KABC) and severity models of KABC crashes; and
- 33,484 crashes for the noninjury (property damage only) crash frequency models (O).

The total numbers of crashes available for the nonfreeway model estimation were:

- 9,579 crashes for the crash frequency models for all types and severities

Table 7 Descriptive statistics for aggregate data

	Comparison Segments (n = 132)				Design Exception Segments (n = 48)			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Tot_KABCO	190.24	533.34	0	5604	411.17	1395.0	0	8110
Tot_KABC	50.02	139.51	0	1470	97.83	316.71	0	1736
Tot_O	140.23	394.71	0	4134	313.33	1080.1	0	6374
LN_LEN	0.70	1.37	-2.30	3.50	0.87	1.53	-2.29	3.17
LN_AADT	9.36	1.58	3.18	11.67	9.09	1.39	5.24	12.15
DE	0.00	0.00	0.00	0.00	1.00	0.00	1.00	1.00
FOUR_TL	0.28	0.45	0.00	1.00	0.25	0.44	0.00	1.00
SIX_TL	0.22	0.42	0.00	1.00	0.08	0.28	0.00	1.00
EIGHT_TEN_TL	0.08	0.27	0.00	1.00	0.10	0.31	0.00	1.00
Aux_Lanes	0.46	0.67	0.00	3.00	0.58	0.74	0.00	2.00
Divided	0.68	0.47	0.00	1.00	1.00	0.00	1.00	1.00
Trav_Divided	0.16	0.37	0.00	1.00	0.25	0.44	0.00	1.00
TWLT	0.20	0.40	0.00	1.00	0.15	0.36	0.00	1.00
Rural	0.54	0.50	0.00	1.00	0.67	0.48	0.00	1.00
HC_MILE	1.50	1.55	0.00	8.69	2.27	3.83	0.00	19.01
Non_FW_INTS_M	2.26	3.80	0.00	18.75	2.99	4.13	0.00	15.38
FW_INTC_M	0.58	0.97	0.00	4.52	0.15	0.33	0.00	1.53
MPH_50_55	0.17	0.38	0.00	1.00	0.31	0.47	0.00	1.00
MPH_60_65	0.45	0.50	0.00	1.00	0.33	0.48	0.00	1.00
MPH_70_80	0.15	0.36	0.00	1.00	0.15	0.36	0.00	1.00
Single_Truck_Ave	10.95	6.30	1.00	40.00	11.69	4.55	0.00	26.25
Combo_Truck_Ave	13.34	11.19	1.25	46.00	14.55	11.54	0.00	38.75

Table 8 Descriptive statistics for nonfreeway data

	Comparison Segments (n = 80)				Design Exception Segments (n = 34)			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Tot_KABCO	89.28	123.09	0	719	72.38	105.55	0	425
Tot_KABC	27.39	39.40	0	189	22.38	35.48	0	154
Tot_O	61.89	86.17	0	537	50.00	70.72	0	271
LN_LEN	1.52	1.83	-2.30	3.50	1.50	1.71	-2.30	3.02
LN_AADT	9.50	9.69	3.18	11.07	9.08	9.11	5.24	10.57
DE	0.00	0.00	0.00	0.00	1.00	0.00	1.00	1.00
FOUR_TL	0.20	0.40	0.00	1.00	0.12	0.33	0.00	1.00
SIX_TL	0.13	0.33	0.00	1.00	0.09	0.29	0.00	1.00
Aux_Lanes	0.53	0.59	0.00	2.00	0.71	0.72	0.00	2.00
Divided	0.48	0.50	0.00	1.00	0.44	0.50	0.00	1.00
Trav_Divided	0.08	0.27	0.00	1.00	0.15	0.36	0.00	1.00
TWLT	0.30	0.46	0.00	1.00	0.21	0.41	0.00	1.00
Rural	0.69	0.47	0.00	1.00	0.71	0.46	0.00	1.00
HC_MILE	1.51	1.81	0.00	8.69	2.75	4.45	0.00	19.01
Non_FW_INTS_M	3.72	4.30	0.00	18.75	4.21	4.35	0.00	15.38
MPH_50_55	0.29	0.46	0.00	1.00	0.44	0.50	0.00	1.00
MPH_60_65	0.34	0.48	0.00	1.00	0.26	0.45	0.00	1.00
Single_Truck_Ave	12.93	6.83	3.25	40.00	12.85	4.31	0.00	26.25
Combo_Truck_Ave	11.82	9.04	1.25	44.00	12.82	10.10	0.00	34.00

Table 9 Descriptive statistics for freeway data

	Comparison Segments (n = 52)				Design Exception Segments (n = 14)			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Tot_KABCO	345.58	816.45	0	5604	1233.9	2445.1	34	8110
Tot_KABC	84.83	213.43	0	1470	281.07	555.33	6	1736
Tot_O	511.66	1922.0	0	13559	1778.7	3681.9	28	13340
LN_LEN	0.96	1.03	-0.65	3.38	1.77	0.82	0.30	3.17
LN_AADT	10.43	0.95	8.51	11.67	10.33	1.29	8.54	12.15
DE	0.00	0.00	0.00	0.00	1.00	0.00	1.00	1.00
SIX_TL	0.37	0.49	0.00	1.00	0.07	0.27	0.00	1.00
EIGHT_TEN_TL	0.19	0.40	0.00	1.00	0.36	0.50	0.00	1.00
Aux_Lanes	0.37	0.77	0.00	3.00	0.29	0.73	0.00	2.00
Trav_Divided	0.29	0.46	0.00	1.00	0.50	0.52	0.00	1.00
Rural	0.31	0.47	0.00	1.00	0.57	0.51	0.00	1.00
HC_MILE	1.48	1.03	0.00	4.52	1.10	0.81	0.19	3.19
FW_INTC_M	1.48	1.03	0.00	4.52	0.51	0.44	0.00	1.53
MPH_70_80	0.38	0.49	0.00	1.00	0.50	0.52	0.00	1.00
Single_Truck_Ave	7.90	3.74	1.00	19.00	8.89	3.95	2.00	15.25
Combo_Truck_Ave	15.68	13.63	2.50	46.00	18.77	13.99	2.50	38.75

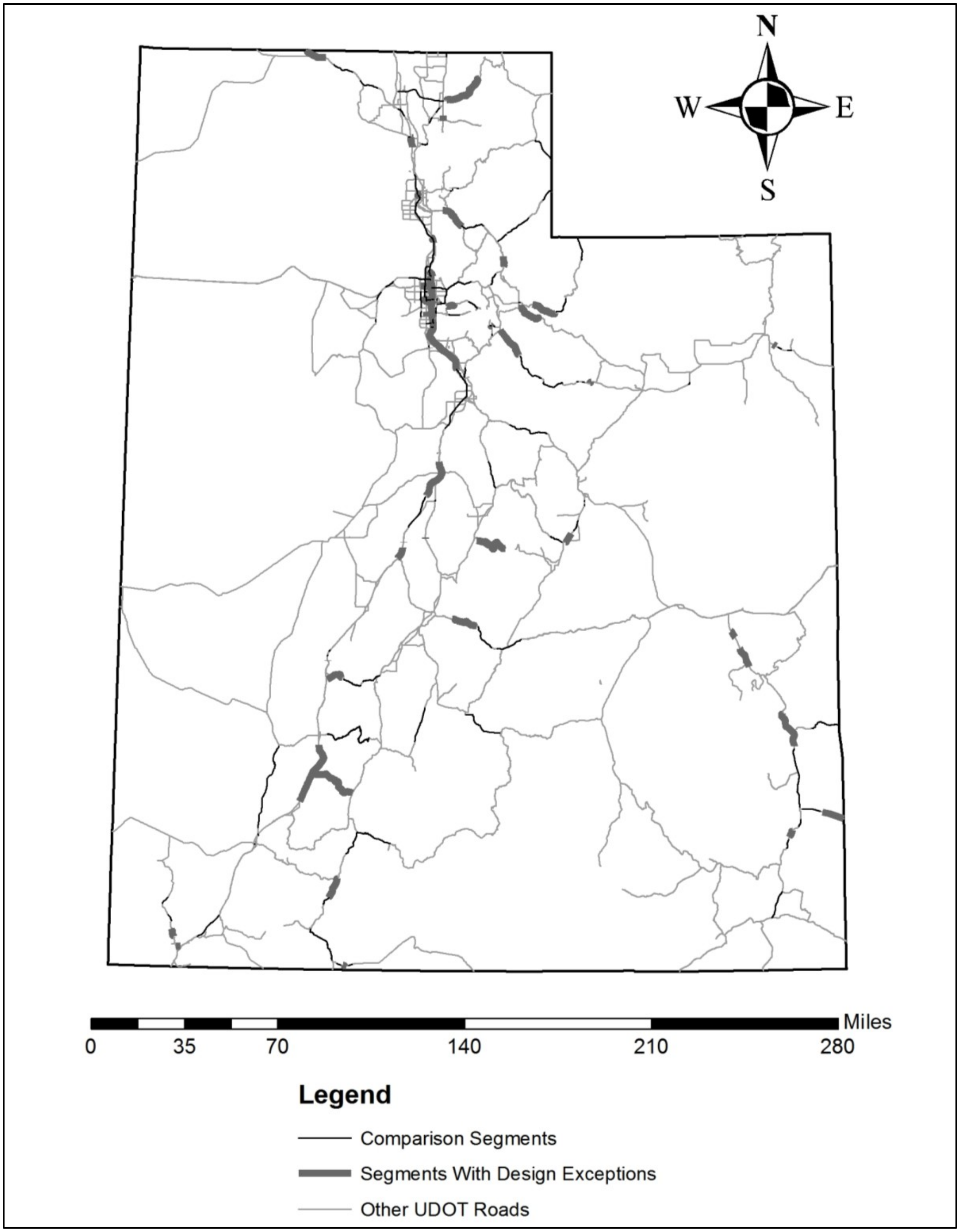

Figure 1 Map of road segments with and without design exceptions

(KABCO) and the severity models of the KABCO crashes;

- 2,948 crashes for the fatal-plus-injury crash frequency models (KABC) and severity models of KABC crashes; and
- 6,631 crashes for the noninjury (property damage only) crash frequency models (O).

The total numbers of crashes available for the freeway model estimation were:

- 35,135 crashes for the crash frequency models for all types and severities (KABCO) and the severity models of the KABCO crashes;
- 8,282 crashes for the fatal-plus-injury crash frequency models (KABC) and severity models of KABC crashes; and
- 26,853 crashes for the noninjury (property damage only) crash frequency models (O).

DATA ANALYSIS

Assessing Comparison Sites with Propensity Scores

Propensity scores were initially analyzed for the 48 (14 freeway, 34 nonfreeway) treatment sites and for 91 comparison sites using the algorithm discussed in the methodology section. Data used for model estimation were disaggregated into two datasets by facility type: freeway or nonfreeway. This was done as freeway and nonfreeway road segments have different characteristics that had the potential to influence selection bias. Also, freeway segments and nonfreeway segments have different potential unobserved covariates that need to be balanced in order to reduce omitted variable bias (e.g., driveway density on nonfreeways). This balancing is the result of the propensity score analysis when separate models are used.

Results of the original propensity score models indicated a need for additional comparison sites to improve 'covariate balance.' Forty-one additional comparison segments were then defined and included in the data set, resulting in 48 treatment sites and 132 comparison locations (52 comparison segments for freeways, 80 comparison segments for nonfreeways). Only the final results of the propensity score analysis are described in this thesis. The numbers of sites by facility type are shown in Table 10. The final estimation results for the binary logistic regression models used to compute the propensity scores for freeways and nonfreeways are provided in Table 11 and Table 12,

Table 10 Number of sites by facility type

Facility Type	Design Exception Locations		Comparison Locations	
	Count	%	Count	%
Urban Freeway	6	13%	34	26%
Urban Major Arterial	4	8%	14	11%
Urban Minor Arterial	6	13%	8	6%
Urban Collector	0	0%	0	0%
Rural Freeway	8	17%	18	14%
Rural Major Arterial	11	23%	33	25%
Rural Minor Arterial	8	17%	12	9%
Rural Collector	5	10%	13	10%
Total	48	100%	132	100%

Table 11 Estimation results for binary logistic regression: freeways

Number of obs = 66						
LR chi2(11) = 46.75						
Prob > chi2 =0.0000						
ρ^2 = 0.6854						
Log likelihood = -10.7308						
Variable	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
LN_AVE_AADT	2.625	2.443	1.070	0.283	-2.164	7.414
Single_Truck_Ave	0.207	0.174	1.190	0.234	-0.134	0.548
Combo_Truck_Ave	-0.083	0.185	-0.450	0.654	-0.445	0.279
MPH_70_80	-15.748	3094.619	-0.010	0.996	-6081.089	6049.594
SIX_TL	10.717	2847.139	0.000	0.997	-5569.572	5591.006
EIGHT_TEN_TL	12.642	2847.138	0.000	0.996	-5567.646	5592.930
Aux_Lanes	-0.584	0.917	-0.640	0.524	-2.382	1.213
Trav_Divided	-0.279	1.962	-0.140	0.887	-4.124	3.566
HC_MILE	9.847	3.815	2.580	0.010	2.370	17.325
Rural	33.379	4205.100	0.010	0.994	-8208.465	8275.223
FW_INTC_M	-11.485	4.036	-2.850	0.004	-19.396	-3.574
Constant	-43.020	2847.263	-0.020	0.988	-5623.552	5537.512

Table 12 Estimation results for binary logistic regression: nonfreeways

Number of obs = 114						
LR chi2(14) = 18.66						
Prob > chi2 =0.1784						
ρ^2 = 0.1343						
Log likelihood = -60.1383						
Variable	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
LN_AVE_AADT	0.091	0.274	0.330	0.739	-0.447	0.629
Single_Truck_Ave	0.000	0.042	0.010	0.993	-0.083	0.083
Combo_Truck_Ave	0.043	0.036	1.200	0.230	-0.027	0.112
MPH_50_55	1.087	0.695	1.560	0.118	-0.275	2.450
MPH_60_65	0.031	0.850	0.040	0.971	-1.636	1.698
FOUR_TL	-0.639	1.221	-0.520	0.600	-3.032	1.753
SIX_TL	-1.031	1.359	-0.760	0.448	-3.695	1.633
Aux_Lanes	0.970	0.530	1.830	0.067	-0.068	2.009
Divided	-1.785	1.248	-1.430	0.153	-4.231	0.661
2WLT	-0.255	1.004	-0.250	0.800	-2.223	1.713
Trav_Divided	0.754	1.173	0.640	0.520	-1.544	3.053
HC_MILE	0.231	0.107	2.150	0.032	0.020	0.441
Rural	-1.744	1.083	-1.610	0.107	-3.866	0.379
Non_FW_INTS_M	0.140	0.084	1.670	0.096	-0.025	0.304
Constant	-1.911	2.734	-0.700	0.485	-7.270	3.449

respectively. The results of the models indicate that the influence of parameters on the probability of a location receiving a design exception were different for nonfreeway segments than for freeway segments.

Propensity scores, defined for this study as the probability of a road segment having a design exception given a set of segment characteristics, were computed using the models in Table 11 and Table 12. Scatter plots of the results of the propensity score analysis for freeways and nonfreeways are shown in Figure 2 and Figure 3, respectively. For the freeway segments, there was a significant difference in the propensity scores for treatment and comparison segments (see Figure 2). The freeway segments in the treatment and comparison groups covered all of the urban freeways in Utah and some

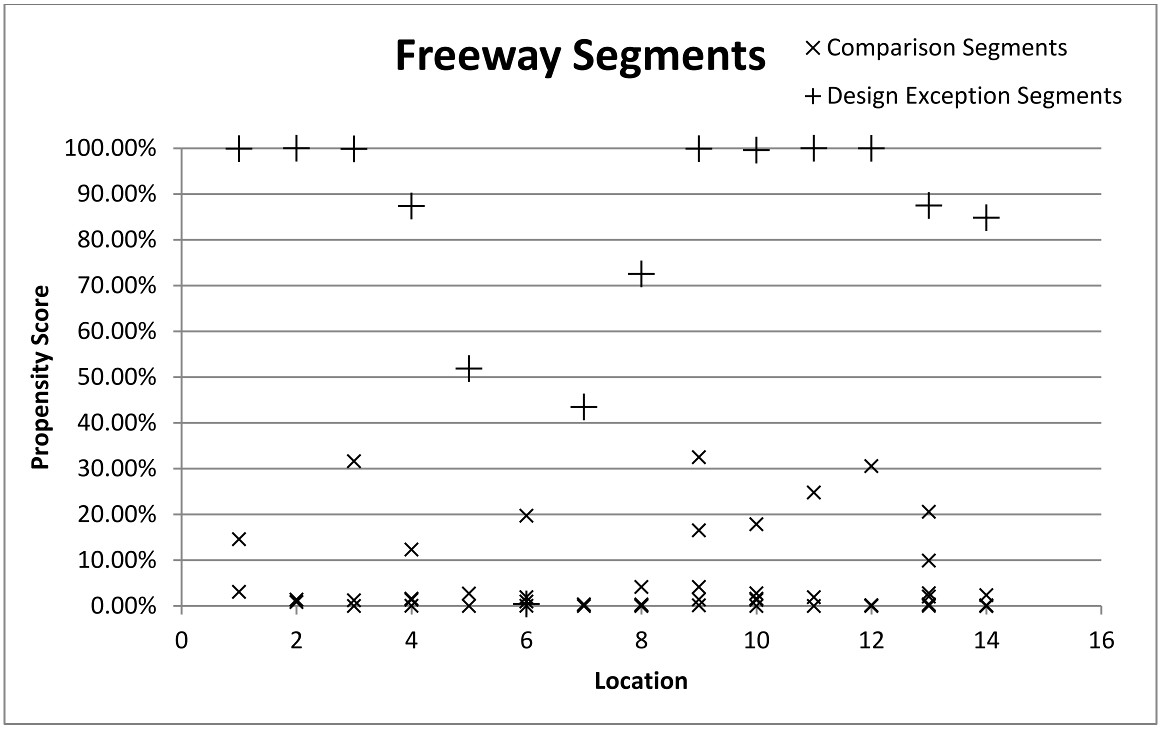

Figure 2 Propensity scores: freeways

rural freeway segments. Due to a lack of additional freeway segments to choose from in urban areas, nothing additional could be done to balance out the propensity scores for the freeway segments. This means that there may be selection bias issues for freeway segments (i.e., freeway segments with design exceptions are inherently different than freeway segments without design exceptions in terms of the covariates specified in Table 11 and Table 12).

Interpretations of the freeway results should consider these differences in propensity scores (see *(42)* for related discussion). The plot of propensity scores for the nonfreeway segments, provided in Figure 3, shows that the propensity scores between treatment and comparison sites were well-balanced. Covariate balance for nonfreeway segments was checked using five strata as described in the methodology section. Initially, LN_AVE_AADT and the number through lanes were used as additional covariates to the

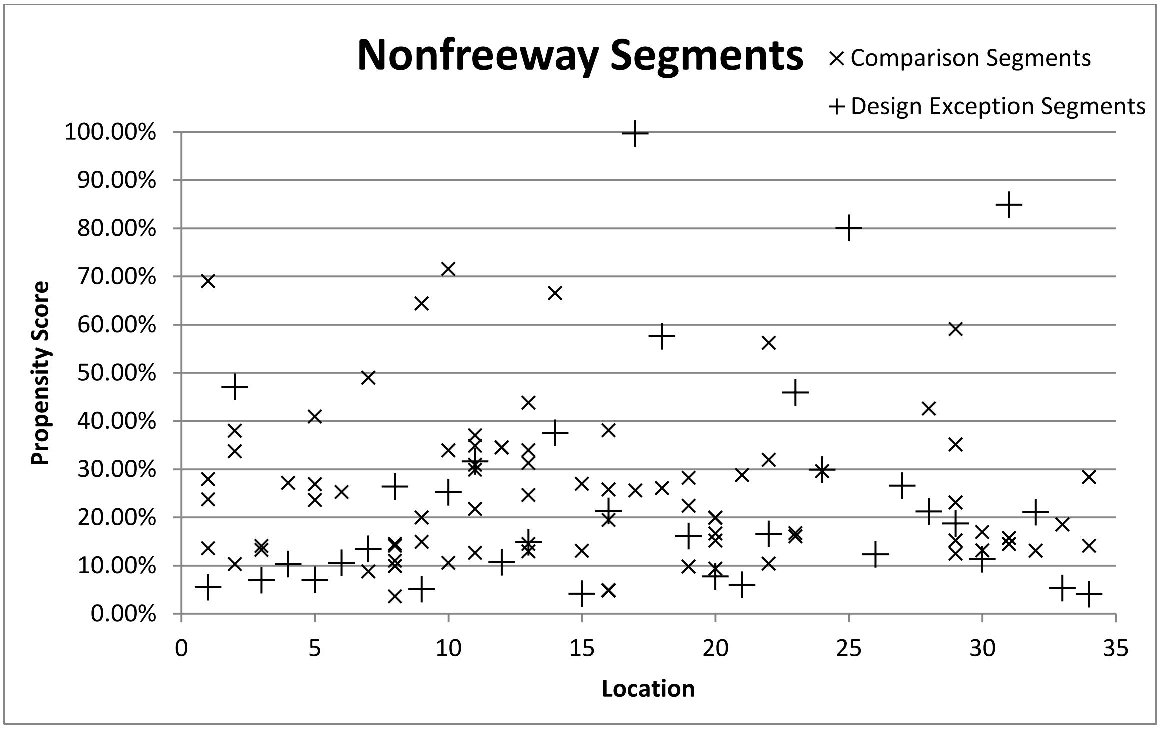

Figure 3 Propensity scores: nonfreeways

propensity score to check for covariate balance. For the final analysis, Aux_Lanes and HC_MILE were used to check covariate balance. These variables were selected for balancing as they were the variables with the most statistically significant parameters. Results indicate that the probability of selection bias in the nonfreeway models is low.

Results: Design Exception Effects on Expected Crash Frequency

Negative Binomial Models

Results of the analysis to estimate the effects of design exceptions on expected crash frequency are presented in this section. The primary analysis method was negative binomial regression modeling with the presence of one or more design exceptions coded as an indicator variable (1 = one or more design exceptions; 0 = no design exceptions). Negative binomial models for aggregate (freeway and nonfreeway data combined), nonfreeway, and freeway segments are presented. Transferability models and tests for the nonfreeway data are also presented. The transferability test was only performed with models using the nonfreeway segments due to the results of the propensity score analysis.

Estimation results for models of total crashes (KABCO), fatal-plus-injury crashes (KABC), and property damage only crashes (O) are provided in Table 13. The models presented in this table were estimated using data from both freeways and nonfreeways with variables that capture the expected differences in safety performance between these facility types. The estimates results for the nonfreeway and freeway models (KABCO, KABC, and O) are provided in Table 14 and Table 15, respectively.

In the aggregate models, the regression parameters associated with the presence of one or more design exceptions were positive but very close to zero in the total, fatal-plus-injury, and property damage only crash models. Parameter estimates were also statistically insignificant (p-value > 0.540 in total crash model, p-value > 0.409 in the fatal-plus-injury crash model, and p-value > 0.552 in the property damage only crash model) for the aggregate models, indicating a very small chance that the parameter is different from zero at all. The parameter estimates show that road segments with one or more design exceptions had the same expected frequency of total crashes (all types and severities), fatal-plus-injury crashes, and property damage only crashes as segments without any design exceptions.

For the nonfreeway models, the regression parameters associated with the presence of one or more design exceptions were very close to zero in the total crash model. This parameter estimate showed that road segments with one or more design exceptions had the same expected frequency of total crashes as segments without any

Table 13 Crash frequency model estimation results for total (KABCO) crashes, fatal-plus-injury (KABC), and property damage only (O) crashes for all road segments

Model	KABCO		KABC		O	
Number of Observations	180		180		180	
LR chi2(19)	371.47		366.11		380.86	
Prob > chi2	0.0000		0.0000		0.0000	
ρ^2	0.1785		0.2212		0.1877	
Log Likelihood	-877.77		-644.49		-824.37	
Variable	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
LN_AADT	**0.921**	**0.064**	**0.865**	**0.071**	**0.924**	**0.065**
DE	0.059	0.097	0.082	0.100	0.058	0.097
Non_FW	**0.481**	**0.235**	**0.529**	**0.229**	*0.451*	*0.237*
FOUR_TL	0.289	0.190	**0.428**	**0.199**	0.297	0.196
SIX_TL	0.387	0.239	**0.485**	**0.244**	*0.415*	*0.244*
EIGHT_TEN_TL	*0.518*	*0.288*	**0.575**	**0.288**	*0.563*	*0.292*
Aux_Lanes	0.072	0.076	0.046	0.073	0.087	0.075
Divided	0.097	0.247	-0.324	0.280	0.286	0.248
Trav_Divided	**-0.367**	**0.175**	-0.089	0.185	**-0.435**	**0.173**
TWLT	-0.049	0.185	*0.321*	*0.179*	-0.253	0.188
Rural	-0.093	0.193	**-0.490**	**0.212**	0.071	0.193
HC_MILE	*0.046*	*0.025*	0.045	0.028	*0.047*	*0.025*
Non_FW_INTS_M	0.009	0.019	-0.001	0.022	0.012	0.019
FW_INTC_M	0.010	0.074	0.003	0.073	0.002	0.073
MPH_50_55	**-0.585**	**0.159**	**-0.635**	**0.160**	**-0.623**	**0.160**
MPH_60_65	**-0.594**	**0.179**	**-0.695**	**0.184**	**-0.606**	**0.179**
MPH_70_80	*-0.529*	*0.271*	-0.346	0.269	**-0.722**	**0.274**
Single_Truck_Ave	0.004	0.008	-0.004	0.009	0.009	0.008
Combo_Truck_Ave	-0.005	0.006	*-0.012*	*0.006*	-0.002	0.006
Constant	**-5.299**	**0.683**	**-5.608**	**0.752**	**-5.852**	**0.698**
LN_LEN	1.000	(offset)	1.000	(offset)	1.000	(offset)
alpha	0.239	0.031	0.195	0.032	0.228	0.031
Statistically significant parameters at 95% are shown in **bold**. Statistically significant parameters at 90% are shown in *italics*.						

Table 14 Crash frequency model estimation results for total (KABCO) crashes, fatal-plus-injury (KABC), and property damage only (O) crashes for nonfreeway road segments

Model	KABCO		KABC		O	
Number of Observations	114		114		114	
LR chi2(15)	232.24		225.15		220.66	
Prob > chi2	0.0000		0.0000		0.0000	
ρ^2	0.1901		0.2420		0.1924	
Log Likelihood	-494.84		-352.63		-463.00	
Variable	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
LN_AADT	**0.936**	**0.079**	**0.922**	**0.092**	**0.930**	**0.084**
DE	-0.001	0.136	0.064	0.145	-0.010	0.140
FOUR_TL	*0.593*	*0.320*	**0.907**	**0.323**	0.493	0.334
SIX_TL	*0.707*	*0.365*	**1.035**	**0.368**	0.618	0.381
Aux_Lanes	-0.034	0.158	-0.163	0.172	0.018	0.162
Divided	0.208	0.331	-0.214	0.362	0.347	0.343
Trav_Divided	-0.435	0.326	-0.295	0.367	-0.453	0.336
TWLT	-0.176	0.270	0.173	0.265	-0.316	0.283
Rural	0.171	0.276	-0.007	0.299	0.236	0.284
HC_MILE	*0.055*	*0.029*	0.049	0.033	*0.055*	*0.029*
Non_FW_INTS_M	0.013	0.022	0.006	0.025	0.017	0.022
MPH_50_55	**-0.568**	**0.181**	**-0.628**	**0.182**	**-0.599**	**0.188**
MPH_60_65	**-0.572**	**0.209**	**-0.644**	**0.211**	**-0.590**	**0.216**
Single_Truck_Ave	0.005	0.011	-0.008	0.011	0.010	0.011
Combo_Truck_Ave	-0.001	0.009	-0.008	0.010	0.001	0.010
Constant	**-5.262**	**0.773**	**-5.997**	**0.876**	**-5.683**	**0.812**
LN_LEN	1.000	(offset)	1.000	(offset)	1.000	(offset)
alpha	0.314	0.051	0.256	0.055	0.32	0.053
Statistically significant parameters at 95% are shown in **bold**. Statistically significant parameters at 90% are shown in *italics*.						

Table 15 Crash frequency model estimation results for total (KABCO) crashes, fatal-plus-injury (KABC), and property damage only (O) crashes for freeway road segments

Model	KABCO		KABC		O	
Number of Observations	66		66		66	
LR chi2(12)	159.84		164.69		162.83	
Prob > chi2	0.0000		0.0000		0.0000	
ρ^2	0.1779		0.2341		0.1884	
Log Likelihood	-369.27		-269.40		-350.74	
Variable	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
LN_AADT	**0.826**	**0.122**	**0.636**	**0.123**	**0.944**	**0.127**
DE	*0.253*	*0.144*	0.216	0.134	0.240	0.147
SIX_TL	-0.087	0.190	-0.313	0.190	0.000	0.191
EIGHT_TEN_TL	0.056	0.225	-0.106	0.224	0.103	0.227
Aux_Lanes	**0.151**	**0.067**	**0.171**	**0.062**	**0.139**	**0.067**
Trav_Divided	-0.275	0.174	0.155	0.182	**-0.392**	**0.175**
Rural	-0.238	0.283	**-0.788**	**0.287**	0.023	0.290
HC_MILE	-0.065	0.136	-0.062	0.131	-0.048	0.140
FW_INTC_M	0.124	0.142	0.109	0.137	0.105	0.145
MPH_70_80	-0.115	0.179	0.026	0.169	-0.236	0.185
Single_Truck_Ave	0.013	0.012	0.015	0.012	0.013	0.012
Combo_Truck_Ave	-0.008	0.009	**-0.023**	**0.008**	0.000	0.009
Constant	**-4.426**	**1.343**	**-3.523**	**1.343**	**-6.108**	**1.397**
LN_LEN	1.000	(offset)	1.000	(offset)	1.000	(offset)
alpha	0.100	0.021	0.070	0.018	0.101	0.021
Statistically significant parameters at 95% are shown in **bold**. Statistically significant parameters at 90% are shown in *italics*.						

design exceptions. The design exception parameter for the fatal-plus-injury crash model was positive and the design exception parameter for the property damage only crash model was negative, indicating potential differences in the expected frequency of these crash types on road segments with and without design exceptions. However, these parameter estimates were statistically insignificant (p-value > 0.991 in total crash model, p-value > 0.653 in the fatal-plus-injury crash model, and p-value > 0.940 in the property damage only crash model), indicating relatively low confidence that the parameter is different from zero at all. The models disaggregated by severity level are discussed at greater length in next section.

The models for the freeway segments indicated that the regression parameters associated with the presence of one or more design exceptions were positive, but close to zero, in all three models. The parameters associated with design exceptions for these models were not statistically significant to 95% confidence, but were much closer to statistical significance than the design exception parameters in either the aggregate or nonfreeway models (p-value > 0.079 in total crash model, p-value > 0.102 in the fatal-plus-injury crash model, and p-value > 0.106 in the property damage only crash model). However, it is important to remember that the propensity score analysis for the freeway segments indicated that the likelihood of selection bias in the data for the freeway segments is high. Thus, the estimates for the parameters in these models are likely to be biased. An example illustrating this possibility is provided in Figure 4. Figure 4 is a plot of the freeway KABCO model predictions and crash observations. It displays the model-estimated number of crashes per mile for road segments with design exceptions, the model-estimated number of crashes per mile for road segments without design

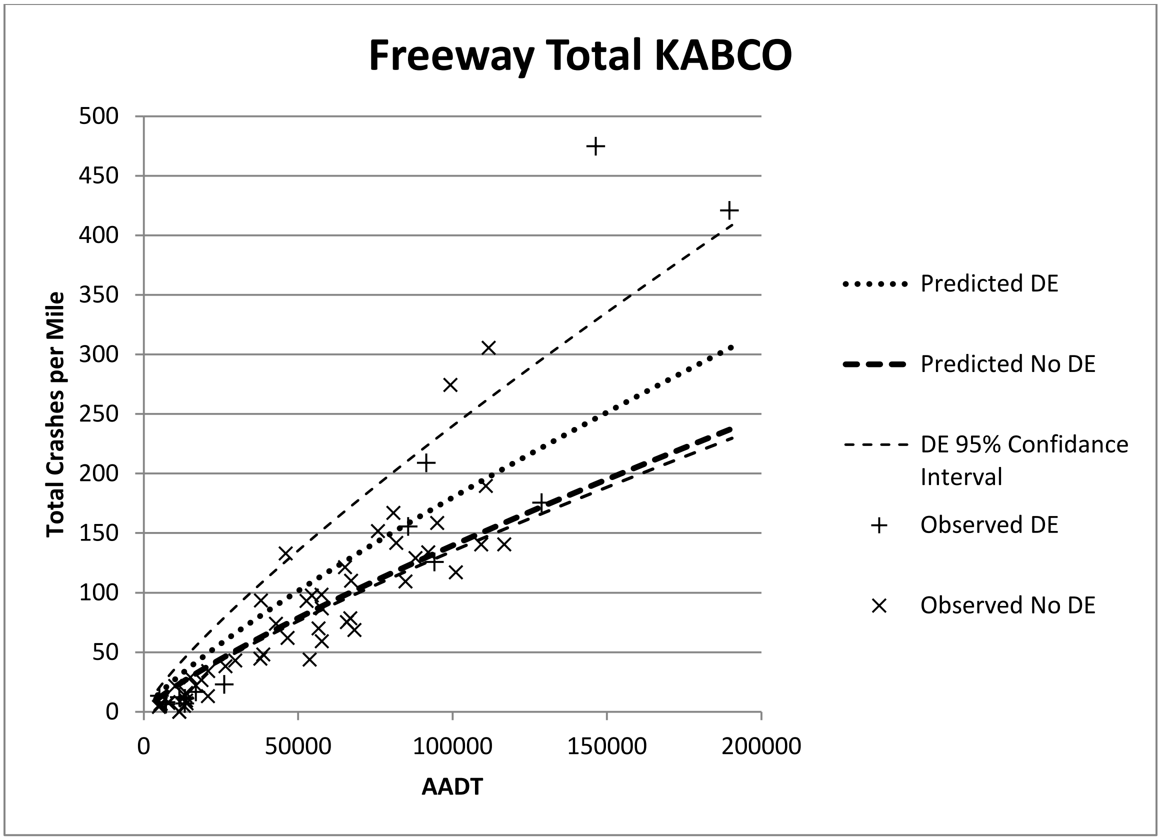

Figure 4 Observed crashes per mile and predicted crashes per mile with and without design exceptions for all crash types and severities on freeway segments

exceptions, the observed crashes per mile for locations with design exceptions, the observed crashes per mile for locations without design exceptions, and the related traffic volumes. In the upper right corner of the figure, there are two design exception locations that are possible ‘outliers.’ There were no other freeway road segments with traffic volumes as high as those two locations. These two observations may or may not be reflective of the safety outcomes of freeway segments with design exceptions and high traffic volumes. As there are no similar comparison segments with these high traffic volumes, the estimation results of the freeway segment models may be biased, particularly in the high-volume region. Additional models need to be explored further in future research.

Transferability Models

The models used to test parameter transferability between design exception sites and comparison sites utilized data only for the nonfreeway segments. Freeway segments were excluded due to the results of the propensity score analysis, which showed that there was not covariate balance between the design exception locations and the comparison locations for freeways. Thus, transferability tests were not run using the freeway data and aggregate data.

Transferability tests were run separately for the total, fatal-plus-injury, and property damage only crash models. The models used for the tests are shown in Table 16, Table 17, and Table 18, respectively. The test results along with the probability that the models are the same are shown in Table 19. The results indicate that the models are not transferable. This finding is consistent with the Indiana study and indicates a different crash generating process at the design exception sites compared to the sites without design exceptions *(6)*.

As discussed in the methodology section, the likelihood ratio test checks the transferability of model parameters. This test is sensitive to the differences in the estimates of parameter effects and to differences in the models due to the effects of the treatment. Thus, the differences in the specified models may be due to the impacts of the design exceptions on crash frequency, but it is also possible that characteristics at locations with design exceptions (e.g., speed, number of lanes, etc.) differ in the way they affect crash frequency than the way they affect crash frequency at locations without design exceptions. This is an interesting finding in that modeling the safety impacts of design exceptions by combining all the data and using an indicator variable to estimate

Table 16 Crash frequency model estimation results for total (KABCO) crashes transferability test using nonfreeway road segments

Model	Full KABCO		NDE KABCO		DE KABCO	
Number of Observations	114		80		34	
LR chi2(14)	232.24		170.490		90.69	
Prob > chi2	0.0000		0.0000		0.0000	
ρ^2	0.1901		0.1966		0.2569	
Log Likelihood	-494.835		-348.466		-131.197	
Variable	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
LN_AADT	**0.936**	**0.079**	**0.884**	**0.087**	**0.931**	**0.160**
Single_Truck_Ave	0.005	0.011	0.001	0.011	0.023	0.027
Combo_Truck_Ave	-0.001	0.009	-0.004	0.011	-0.017	0.017
MPH_50_55	**-0.568**	**0.180**	-0.306	0.220	**-0.759**	**0.306**
MPH_60_65	**-0.572**	**0.208**	*-0.367*	*0.221*	-0.239	0.520
FOUR_TL	*0.594*	*0.320*	0.485	0.396	0.780	0.486
SIX_TL	**0.708**	**0.361**	**0.937**	**0.474**	0.086	0.534
Aux_Lanes	-0.034	0.158	**0.414**	**0.200**	**-0.798**	**0.214**
Divided	0.208	0.331	-0.131	0.408	-0.102	0.583
2WLT	-0.175	0.267	-0.026	0.375	-0.200	0.369
Trav_Divided	-0.434	0.324	-0.387	0.400	-0.069	0.631
HC_MILE	0.055	0.028	0.093	0.046	0.023	0.034
Rural	0.172	0.272	0.014	0.344	-0.251	0.471
Non_FW_INTS_M	0.013	0.021	0.022	0.026	0.048	0.037
Constant	**-5.262**	**0.772**	**-4.992**	**0.842**	**-4.448**	**1.474**
LN_LEN	1.000	(offset)	1.000	(offset)	1.000	(offset)
alpha	0.314	0.051	0.269	0.057	0.149	0.047
Statistically significant parameters at 95% are shown in **bold**. Statistically significant parameters at 90% are shown in *italics*.						

Table 17 Crash frequency model estimation results for fatal-plus-injury (KABC) crashes transferability test using nonfreeway road segments

Model	Full KABC		NDE KABC		DE KABC	
Number of Observations	114		80		34	
LR chi2(14)	224.96		163.980		92.1	
Prob > chi2	0.0000		0.0000		0.0000	
ρ^2	0.2418		0.2479		0.3433	
Log Likelihood	-352.732		-248.776		-88.103	
Variable	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
LN_AADT	**0.920**	**0.091**	**0.827**	**0.102**	**1.106**	**0.138**
Single_Truck_Ave	-0.008	0.011	-0.012	0.012	-0.041	0.026
Combo_Truck_Ave	-0.007	0.009	-0.017	0.011	**-0.040**	**0.016**
MPH_50_55	**-0.620**	**0.181**	*-0.411*	*0.212*	*-0.496*	*0.283*
MPH_60_65	**-0.650**	**0.211**	**-0.440**	**0.222**	0.223	0.502
FOUR_TL	**0.896**	**0.321**	*0.855*	*0.442*	0.577	0.370
SIX_TL	**1.011**	**0.363**	**1.429**	**0.522**	0.182	0.439
Aux_Lanes	-0.154	0.171	0.283	0.227	**-1.014**	**0.239**
Divided	-0.210	0.362	-0.736	0.454	0.230	0.789
2WLT	-0.007	0.261	**0.798**	**0.375**	**-1.178**	**0.300**
Trav_Divided	-0.327	0.361	-0.086	0.480	-1.313	0.824
HC_MILE	0.052	0.032	0.078	0.051	-0.033	0.037
Rural	-0.034	0.293	-0.071	0.353	-0.575	0.659
Non_FW_INTS_M	0.008	0.024	0.009	0.029	-0.043	0.041
Constant	**-5.960**	**0.871**	**-5.301**	**0.969**	**-5.644**	**1.396**
LN_LEN	1.000	(offset)	1.000	(offset)	1.000	(offset)
alpha	0.257	0.055	0.207	0.057	0.037	0.043
Statistically significant parameters at 95% are shown in **bold**. Statistically significant parameters at 90% are shown in *italics*.						

Table 18 Crash frequency model estimation results for property damage only (O) crashes transferability test using nonfreeway road segments

Model	Full O		NDE O		DE O	
Number of Observations	114		80		34	
LR chi2(14)	220.65		169.280		82.07	
Prob > chi2	0.0000		0.0000		0.0000	
ρ^2	0.1924		0.2075		0.2494	
Log Likelihood	-463.001		-323.280		-123.516	
Variable	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
LN_AADT	**0.930**	**0.084**	**0.880**	**0.087**	**0.847**	**0.177**
Single_Truck_Ave	0.010	0.011	0.007	0.011	0.036	0.030
Combo_Truck_Ave	0.001	0.009	0.000	0.011	-0.019	0.019
MPH_50_55	**-0.600**	**0.187**	*-0.370*	*0.214*	**-0.885**	**0.340**
MPH_60_65	**-0.589**	**0.216**	*-0.408*	*0.215*	-0.288	0.572
FOUR_TL	0.494	0.333	0.339	0.391	0.810	0.547
SIX_TL	*0.622*	*0.377*	*0.791*	*0.465*	-0.093	0.608
Aux_Lanes	0.017	0.161	**0.474**	**0.192**	**-0.792**	**0.236**
Divided	0.348	0.343	0.123	0.398	-0.119	0.643
2WLT	-0.313	0.280	-0.258	0.363	-0.260	0.413
Trav_Divided	-0.450	0.334	-0.500	0.387	0.150	0.699
HC_MILE	0.054	0.029	*0.089*	*0.046*	0.023	0.037
Rural	0.239	0.280	0.025	0.335	-0.142	0.517
Non_FW_INTS_M	0.016	0.022	0.027	0.026	0.063	0.041
Constant	**-5.687**	**0.811**	**-5.428**	**0.840**	**-4.246**	**1.634**
LN_LEN	1.000	(offset)	1.000	(offset)	1.000	(offset)
alpha	0.320	0.053	0.241	0.054	0.176	0.056
Statistically significant parameters at 95% are shown in **bold**. Statistically significant parameters at 90% are shown in *italics*.						

Table 19 Transferability test results

Model	Full	DE	P-Value
	Log-Likelihood	Log-Likelihood	
KABCO	-494.835	-131.197	0.007
KABC	-352.732	-88.103	0.004
O	-463.001	-123.516	0.004

the effects of design exceptions assumes that all parameters (other than the treatment indicator for design exceptions) have the same effect on crash generation. If this is not the case, the models may incorrectly estimate the actual impacts of design exceptions on safety. Specifying the interaction of design exception presence with other variables in the model could be another way to explore this issue, but the current sample size is too small to explore this option.

Results: Design Exception Effects on Expected Crash Severity

Results of the analysis to estimate the effects of design exceptions on expected crash severity are presented in this section for the aggregate, nonfreeway, and freeway data. Three alternative analysis methods were used: 1) computing severity distributions at locations with and without design exceptions, 2) estimating separate negative binomial regression models by severity level, and 3) estimating multinomial logit models. The first method is analogous to the method used to compute severity distributions in the Highway Safety Manual predictive method for rural, two-lane roads. Results of this approach for the aggregate, nonfreeway, and freeway segments are provided in Table 20, Table 21, and Table 22, respectively. The severity distributions indicate that crashes on road segments with design exceptions tend to be less severe than crashes on road segments without design exceptions for the aggregate and freeway segments (Table 20 and Table 22). The results for the nonfreeway segments (Table 21) indicate that nonfreeway road segments with design exceptions tend to be slightly more severe than the nonfreeway segments without design exceptions. The percentages of crashes that result in a fatality or any level of injury on road segments with design exceptions are lower than those same percentages on road segments without design exceptions for the aggregate and freeway

Table 20 Default severity distributions for all road segments with and without design exceptions

	Design Exception Locations		Comparison Locations		All Locations Combined	
	Total	%	Total	%	Total	%
K	49	0.25%	135	0.54%	184	0.41%
A	264	1.34%	446	1.79%	710	1.59%
B	1,490	7.55%	2,180	8.73%	3,670	8.21%
C	2,893	14.66%	3,773	15.10%	6,666	14.91%
O	15,035	76.20%	18,449	73.84%	33,484	74.88%

Table 21 Default severity distributions for nonfreeway road segments with and without design exceptions

	Design Exception Locations		Comparison Locations		All Locations Combined	
	Total	%	Total	%	Total	%
K	15	0.61%	42	0.59%	57	0.60%
A	58	2.36%	160	2.25%	218	2.28%
B	244	9.94%	746	10.47%	990	10.34%
C	442	18.00%	1,241	17.42%	1683	17.57%
O	1,696	69.08%	4,935	69.27%	6631	69.22%

Table 22 Default severity distributions for freeway road segments with and without design exceptions

	Design Exception Locations		Comparison Locations		All Locations Combined	
	Total	%	Total	%	Total	%
K	34	0.20%	93	0.52%	127	0.36%
A	205	1.19%	290	1.62%	495	1.41%
B	1,245	7.21%	1,447	8.07%	2,692	7.65%
C	2,450	14.19%	2,542	14.18%	4,992	14.18%
O	13,337	77.22%	13,552	75.61%	26,889	76.40%

data. The opposite is true for the nonfreeway data. The percentage of crashes resulting in property damage only is therefore higher on design exception segments for the aggregate and freeway segments, but lower for the nonfreeway segments. This default distribution approach to crash severity has one major disadvantage: it does not capture additional differences between road segments with and without design exceptions that may also impact the crash severity distributions (e.g., traffic volumes). The second method of estimating separate negative binomial regression models by severity level is analogous to the method used to compute severity distributions in the *Highway Safety Manual* predictive method for rural, multilane roads and urban and suburban arterials. The three frequency models presented in the previous section are applied independently to predict average crash frequencies for total (KABCO), fatal-plus-injury (KABC), and property damage only (O) crashes. Adjustments are then made to the fatal-plus-injury and property damage only predictions so that they sum to equal the ‘total’ crash prediction. Results of this approach, summarized in Figure 5, Figure 6, and Figure 7, show practically no difference in crash severity when comparing locations with and without design exceptions.

Approximately 25% of predicted crashes result in a fatality or some level of injury; approximately 75% of predicted crashes result in property damage only. This is true for all of the models used.

The third analysis method used was multinomial logistic regression modeling with the presence of one or more design exceptions coded as an indicator variable (1 = one or more design exceptions; 0 = no design exceptions). The methodology is described in greater detail in the methodology section. The road segments for this effort are the

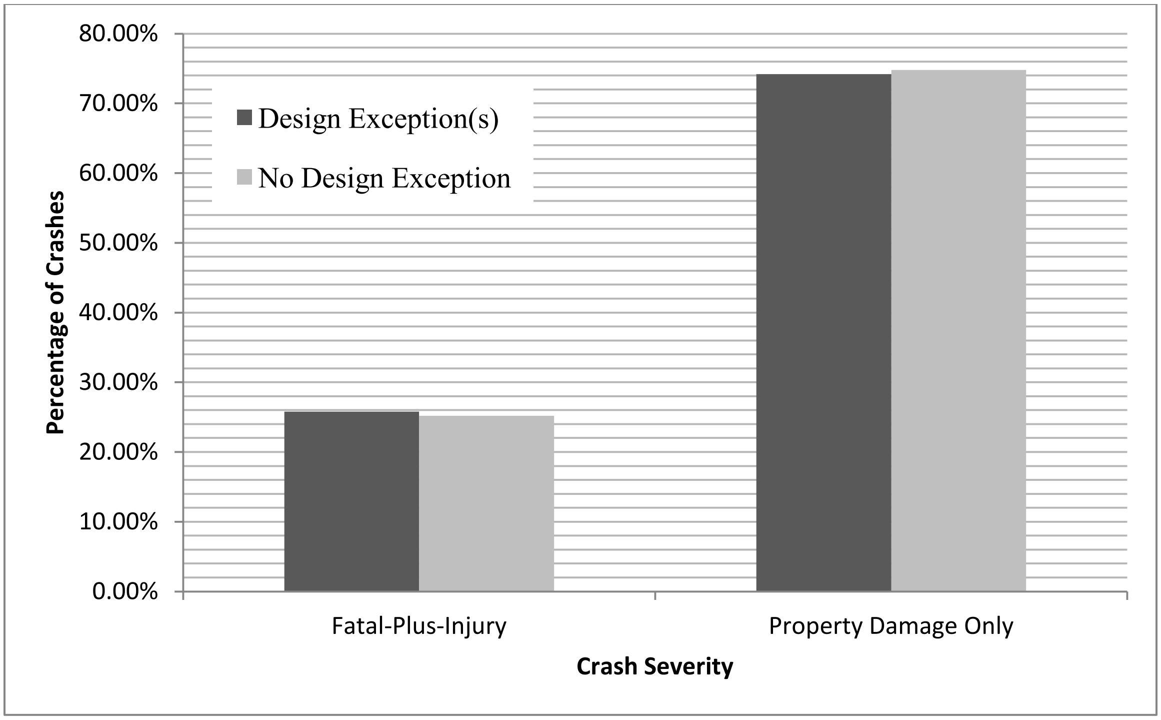

Figure 5 Distributions of injury and noninjury crashes on road segments with and without design exceptions (based on aggregate crash frequency models)

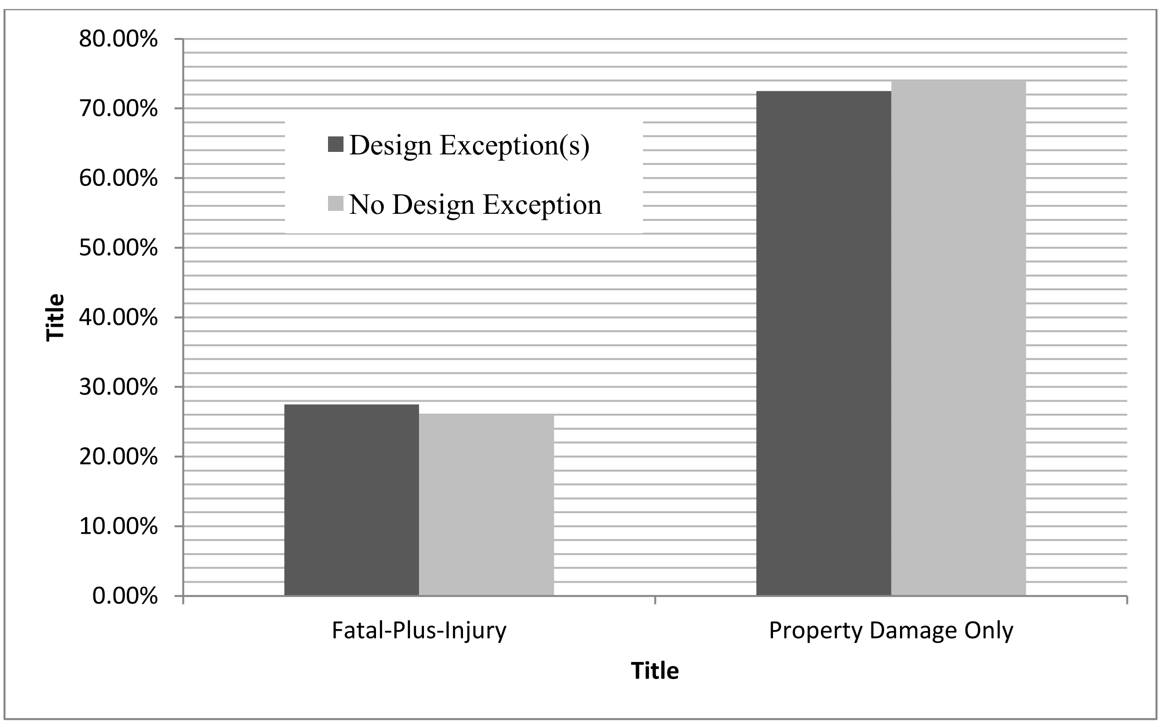

Figure 6 Distributions of injury and noninjury crashes on road segments with and without design exceptions (based on nonfreeway crash frequency models)

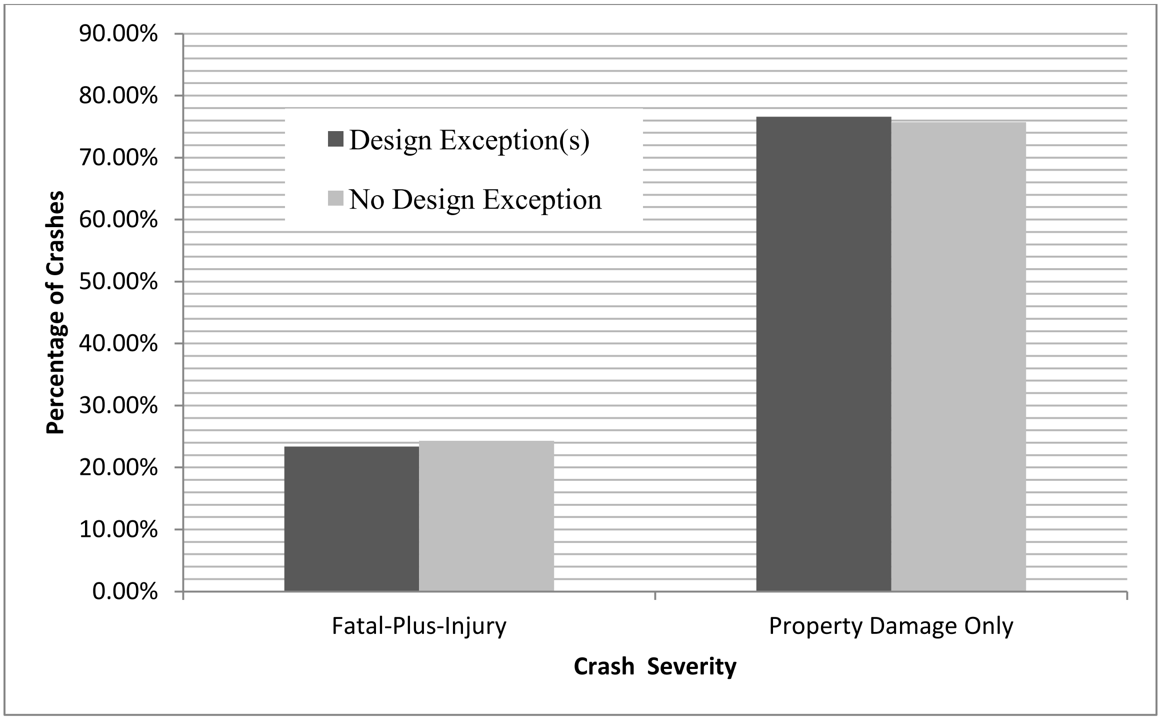

Figure 7 Distributions of injury and noninjury crashes on road segments with and without design exceptions (based on freeway crash frequency models)

same as those used for the frequency analysis. The crash severity database itself is set up so that one row equals one crash. The databases used for model estimation included up to nearly 45,000 crashes for the aggregate data. The database for the nonfreeway model estimation included nearly 9,600 crashes. The database for the freeway model estimation included just over 35,000 crashes.

Estimation results for the aggregate multinomial logit models of total crashes (all types and severities) and fatal-plus-injury crashes (all crash types and severity of fatal or injury) are provided in Table 23 and Table 24 for the aggregate models, Table 25 and Table 26 for the nonfreeway models, and Table 27 and Table 28 for the freeway models. The models presented in these tables were estimated using data from both freeways and nonfreeways with variables that capture the expected differences in safety performance

Table 23 Aggregate crash severity model estimation results for total (KABCO) crashes

Number of Observations = 44714, LR Chi2(76) = 805.97				
Prob > Chi2 = 0.0000, ρ^2 = 0.0114, Log Likelihood = -35095.848, Base Outcome = PDO				
Severity	Possible Injury		Nonincapacitating Injury	
Variable	Coefficient	Std. Error	Coefficient	Std. Error
LN_AADT	-0.051	0.047	*-0.097*	*0.054*
DE	**-0.080**	**0.040**	-0.068	0.050
Non_FW	0.080	0.124	-0.015	0.156
FOUR_TL	**0.525**	**0.167**	**0.406**	**0.191**
SIX_TL	**0.368**	**0.180**	0.006	0.207
EIGHT_TEN_TL	**0.443**	**0.190**	0.101	0.220
Aux_Lanes	**-0.059**	**0.027**	**-0.090**	**0.036**
Divided	-0.209	0.177	**-0.511**	**0.207**
Trav_Divided	0.012	0.077	**0.275**	**0.092**
TWLT	0.060	0.081	**0.276**	**0.106**
Rural	**-0.315**	**0.130**	**-0.459**	**0.149**
HC_MILE	0.013	0.017	0.015	0.021
Non_FW_INTS_M	**0.039**	**0.011**	**0.037**	**0.014**
FW_INTC_M	**-0.085**	**0.039**	-0.022	0.049
MPH_50_55	**0.172**	**0.082**	**0.382**	**0.102**
MPH_60_65	0.025	0.101	*0.208*	*0.122*
MPH_70_80	-0.157	0.138	*0.287*	*0.164*
Single_Truck_Ave	**-0.008**	**0.004**	0.001	0.005
Combo_Truck_Ave	-0.006	0.004	-0.001	0.005
Constant	**-1.064**	**0.522**	-0.968	0.607
Severity	Incapacitating Injury		Fatal	
Variable	Coefficient	Std. Error	Coefficient	Std. Error
LN_AADT	-0.144	0.097	-0.263	0.172
DE	-0.122	0.105	-0.286	0.204
Non_FW	-0.464	0.344	-0.422	0.645
FOUR_TL	*0.737*	*0.439*	**-1.262**	**0.573**
SIX_TL	0.298	0.476	**-1.779**	**0.692**
EIGHT_TEN_TL	0.241	0.498	**-1.983**	**0.746**
Aux_Lanes	-0.025	0.078	-0.103	0.146
Divided	**-1.649**	**0.480**	-0.922	0.699
Trav_Divided	**0.553**	**0.191**	0.562	0.360
TWLT	**0.721**	**0.259**	0.203	0.550
Rural	-0.241	0.295	*-0.926*	*0.523*
HC_MILE	0.030	0.041	*-0.221*	*0.116*
Non_FW_INTS_M	0.011	0.031	0.039	0.083
FW_INTC_M	-0.065	0.104	0.261	0.191
MPH_50_55	0.332	0.207	0.644	0.531
MPH_60_65	0.234	0.238	0.876	0.534
MPH_70_80	*0.562*	*0.327*	*1.243*	*0.651*
Single_Truck_Ave	0.000	0.010	**-0.057**	**0.021**
Combo_Truck_Ave	*-0.015*	*0.009*	0.012	0.013
Constant	-1.175	1.121	-0.105	1.949
Statistically significant parameters at 95% are shown in **bold**. Statistically significant parameters at 90% are shown in *italics*.				

Table 24 Aggregate crash severity model estimation results for fatal-plus-injury (KABC) crashes

Number of Observations = 11230, LR Chi2(57) = 452.48				
Prob > Chi2 = 0.0000, ρ2 = 0.02180, Log Likelihood = -10071.922, Base Outcome = Poss. Inj.				
Severity	Nonincapacitating Injury		Incapacitating Injury	
Variable	Coefficient	Std. Error	Coefficient	Std. Error
LN_AADT	-0.061	0.068	-0.116	0.107
DE	0.018	0.060	-0.033	0.112
	-0.128	0.186	-0.574	0.360
FOUR_TL	-0.120	0.235	0.183	0.460
SIX_TL	-0.346	0.252	-0.066	0.495
EIGHT_TEN_TL	-0.347	0.267	-0.220	0.519
Aux_Lanes	-0.030	0.043	0.037	0.082
Divided	-0.273	0.257	**-1.364**	**0.504**
Trav_Divided	*0.215*	*0.118*	**0.462**	**0.211**
TWLT	*0.202*	*0.121*	**0.629**	**0.264**
Rural	-0.173	0.193	-0.007	0.333
HC_MILE	0.003	0.026	0.018	0.045
Non_FW_INTS_M	-0.002	0.017	-0.025	0.033
FW_INTC_M	0.054	0.061	0.000	0.112
MPH_50_55	0.200	0.119	0.151	0.215
MPH_60_65	0.176	0.146	0.208	0.253
MPH_70_80	0.393	0.198	*0.661*	*0.346*
Single_Truck_Ave	0.010	0.006	0.011	0.011
Combo_Truck_Ave	0.007	0.006	-0.003	0.009
Constant	0.240	0.759	0.048	1.237
Severity	Fatal			
Variable	Coefficient	Std. Error		
LN_AADT	-0.277	0.178		
DE	-0.203	0.209		
	-0.689	0.666		
FOUR_TL	**-1.806**	**0.601**		
SIX_TL	**-2.090**	**0.714**		
EIGHT_TEN_TL	**-2.421**	**0.768**		
Aux_Lanes	-0.074	0.149		
Divided	-0.635	0.726		
Trav_Divided	0.395	0.386		
TWLT	0.136	0.571		
Rural	-0.715	0.578		
HC_MILE	**-0.238**	**0.118**		
Non_FW_INTS_M	0.010	0.085		
FW_INTC_M	0.290	0.196		
MPH_50_55	0.484	0.545		
MPH_60_65	0.842	0.556		
MPH_70_80	*1.291*	*0.670*		
Single_Truck_Ave	**-0.047**	**0.022**		
Combo_Truck_Ave	*0.026*	*0.013*		
Constant	1.648	2.069		
Statistically significant parameters at 95% are shown in **bold**. Statistically significant parameters at 90% are shown in *italics*.				

Table 25 Nonfreeway crash severity model estimation results for total (KABCO) crashes

Number of Observations = 9579, LR Chi2(60) = 337.57				
Prob > Chi2 = 0.0000, ρ^2 = 0.0193, Log Likelihood = -8560.623, Base Outcome = PDO				
Severity	Possible Injury		Nonincapacitating Injury	
Variable	Coefficient	Std. Error	Coefficient	Std. Error
LN_AADT	-0.004	0.075	-0.100	0.083
DE	**0.249**	**0.118**	-0.197	0.148
Single_Truck_Ave	**-0.023**	**0.006**	-0.008	0.007
Combo_Truck_Ave	**-0.014**	**0.007**	0.003	0.008
MPH_50_55	0.006	0.125	*-0.282*	*0.153*
MPH_60_65	-0.121	0.083	**-0.285**	**0.103**
FOUR_TL	*0.399*	*0.238*	0.297	0.290
SIX_TL	0.432	0.275	-0.084	0.332
Aux_Lanes	-0.032	0.105	-0.014	0.122
Divided	**-0.319**	**0.159**	-0.012	0.186
2WLT	**0.282**	**0.134**	0.100	0.168
Trav_Divided	-0.062	0.211	**-0.624**	**0.280**
HC_MILE	0.011	0.020	0.058	0.024
Rural	-0.128	0.241	-0.259	0.281
Non_FW_INTS_M	*0.023*	*0.014*	**0.052**	**0.016**
Constant	*-1.149*	*0.694*	-0.963	0.763
Severity	Incapacitating Injury		Fatal	
Variable	Coefficient	Std. Error	Coefficient	Std. Error
LN_AADT	-0.035	0.144	*0.493*	*0.299*
DE	0.140	0.315	1.010	0.791
Single_Truck_Ave	0.002	0.014	*-0.055*	*0.033*
Combo_Truck_Ave	0.003	0.014	-0.002	0.021
MPH_50_55	-0.362	0.334	-1.827	1.229
MPH_60_65	-0.235	0.201	-0.821	0.513
FOUR_TL	0.087	0.567	**-1.901**	**0.950**
SIX_TL	-0.425	0.641	**-3.218**	**1.371**
Aux_Lanes	-0.375	0.246	**-0.938**	**0.386**
Divided	-0.458	0.363	-1.278	0.840
2WLT	*0.644*	*0.369*	0.244	0.952
Trav_Divided	0.115	0.583	0.536	1.290
HC_MILE	*0.086*	*0.046*	**-0.296**	**0.123**
Rural	-0.107	0.550	-0.759	0.940
Non_FW_INTS_M	-0.005	0.038	-0.039	0.103
Constant	**-2.748**	**1.349**	*-5.306*	*2.807*
Statistically significant parameters at 95% are shown in **bold**. Statistically significant parameters at 90% are shown in *italics*.				

Table 26 Nonfreeway crash severity model estimation results for fatal-plus-injury (KABC) crashes

Number of Observations = 2948, LR Chi2(45) = 202.56				
Prob > Chi2 = 0.0000, ρ2 = 0.0360, Log Likelihood = -2715.058, Base Outcome = Poss. Inj.				
Severity	Nonincapacitating Injury		Incapacitating Injury	
Variable	Coefficient	Std. Error	Coefficient	Std. Error
LN_AADT	-0.133	0.105	-0.067	0.160
DE	**-0.450**	**0.174**	-0.123	0.330
Single_Truck_Ave	*0.014*	*0.009*	*0.025*	*0.014*
Combo_Truck_Ave	**0.019**	**0.009**	0.024	0.015
MPH_50_55	-0.280	0.183	-0.281	0.353
MPH_60_65	-0.153	0.119	-0.088	0.211
FOUR_TL	-0.076	0.352	-0.339	0.611
SIX_TL	-0.432	0.397	-0.828	0.678
Aux_Lanes	0.045	0.159	-0.366	0.280
Divided	0.306	0.230	-0.162	0.392
2WLT	-0.172	0.204	0.437	0.395
Trav_Divided	*-0.607*	*0.337*	0.181	0.630
HC_MILE	0.049	0.030	0.080	0.052
Rural	-0.136	0.366	-0.114	0.621
Non_FW_INTS_M	0.030	0.019	-0.027	0.040
Constant	0.479	0.966	-1.297	1.492
Severity	Fatal			
Variable	Coefficient	Std. Error		
LN_AADT	0.470	0.313		
DE	0.747	0.798		
Single_Truck_Ave	-0.027	0.032		
Combo_Truck_Ave	0.024	0.022		
MPH_50_55	-1.560	1.258		
MPH_60_65	-0.684	0.527		
FOUR_TL	**-2.336**	**0.984**		
SIX_TL	**-3.508**	**1.343**		
Aux_Lanes	**-1.013**	**0.420**		
Divided	-1.079	0.859		
2WLT	0.229	0.965		
Trav_Divided	0.726	1.346		
HC_MILE	**-0.307**	**0.125**		
Rural	-0.808	0.997		
Non_FW_INTS_M	-0.067	0.108		
Constant	-3.993	2.927		
Statistically significant parameters at 95% are shown in **bold**. Statistically significant parameters at 90% are shown in *italics*.				

Table 27 Freeway crash severity model estimation results for total (KABCO) crashes

Number of Observations = 35135, LR Chi2(48) = 332.29				
Prob > Chi2 = 0.0000, ρ^2 = 0.0062, Log Likelihood = -26566.874, Base Outcome = PDO				
Severity	Possible Injury		Nonincapacitating Injury	
Variable	Coefficient	Std. Error	Coefficient	Std. Error
LN_AADT	0.097	0.090	**-0.217**	**0.106**
DE	*-0.102*	*0.059*	0.091	0.074
SIX_TL	-0.122	0.121	**-0.373**	**0.138**
EIGHT_TEN_TL	-0.108	0.140	-0.195	0.165
Aux_Lanes	0.000	0.034	*-0.080*	*0.045*
Trav_Divided	-0.080	0.102	**0.433**	**0.125**
Rural	-0.040	0.199	**-0.632**	**0.233**
HC_MILE	*-0.128*	*0.070*	**-0.220**	**0.088**
FW_INTC_M	0.057	0.080	**0.238**	**0.100**
MPH_70_80	*-0.174*	*0.105*	0.160	0.124
Single_Truck_Ave	0.000	0.007	0.000	0.008
Combo_Truck_Ave	0.001	0.007	-0.009	0.008
Constant	**-2.523**	**1.017**	0.416	1.193
Severity	Incapacitating Injury		Fatal	
Variable	Coefficient	Std. Error	Coefficient	Std. Error
LN_AADT	**-0.513**	**0.210**	**-0.842**	**0.335**
DE	-0.049	0.162	-0.490	0.317
SIX_TL	**-0.627**	**0.279**	-0.380	0.450
EIGHT_TEN_TL	-0.514	0.331	-0.283	0.543
Aux_Lanes	-0.022	0.096	-0.010	0.165
Trav_Divided	**0.557**	**0.248**	0.513	0.414
Rural	-0.189	0.452	-0.903	0.726
HC_MILE	-0.243	0.196	0.022	0.348
FW_INTC_M	0.170	0.219	-0.039	0.368
MPH_70_80	0.145	0.249	0.162	0.410
Single_Truck_Ave	0.009	0.017	-0.036	0.028
Combo_Truck_Ave	**-0.047**	**0.016**	-0.015	0.023
Constant	2.648	2.377	4.986	3.754
Statistically significant parameters at 95% are shown in **bold**. Statistically significant parameters at 90% are shown in *italics*.				

Table 28 Freeway crash severity model estimation results for fatal-plus-injury (KABC) crashes

Number of Observations = 8282, LR Chi2(36) = 294.14				
Prob > Chi2 = 0.0000, ρ2 = 0.0179, Log Likelihood = -7367.041, Base Outcome = Poss. Inj.				
Severity	Noninncapacitating Injury		Incapacitating Injury	
Variable	Coefficient	Std. Error	Coefficient	Std. Error
LN_AADT	**-0.272**	**0.135**	**-0.549**	**0.233**
DE	**0.206**	**0.091**	0.057	0.172
SIX_TL	-0.233	0.175	-0.474	0.302
EIGHT_TEN_TL	-0.105	0.206	-0.431	0.356
Aux_Lanes	-0.074	0.055	-0.013	0.102
Trav_Divided	**0.500**	**0.163**	**0.585**	**0.282**
Rural	**-0.632**	**0.311**	-0.197	0.523
HC_MILE	-0.110	0.105	-0.136	0.202
FW_INTC_M	0.198	0.121	0.120	0.228
MPH_70_80	**0.314**	**0.154**	0.289	0.266
Single_Truck_Ave	-0.001	0.011	0.007	0.019
Combo_Truck_Ave	-0.004	0.010	**-0.039**	**0.017**
Constant	2.444	1.534	*4.460*	*2.663*
Severity	Fatal			
Variable	Coefficient	Std. Error		
LN_AADT	**-0.907**	**0.355**		
DE	-0.364	0.319		
SIX_TL	-0.238	0.466		
EIGHT_TEN_TL	-0.207	0.558		
Aux_Lanes	-0.014	0.169		
Trav_Divided	0.503	0.456		
Rural	-0.914	0.800		
HC_MILE	0.072	0.345		
FW_INTC_M	-0.038	0.367		
MPH_70_80	0.286	0.418		
Single_Truck_Ave	-0.039	0.030		
Combo_Truck_Ave	-0.007	0.024		
Constant	*7.173*	*4.019*		
Statistically significant parameters at 95% are shown in **bold**. Statistically significant parameters at 90% are shown in *italics*.				

between these facility types. Hausman tests were used to test the IIA assumption for each of the models. The results of the hausman tests showed that the IIA assumption was valid (p-values > 0.98).

The multinomial logit model estimation results show that the parameters associated with the presence of one or more design exceptions were not statistically significant (p-values ranging from 0.270 to 0.771) in the aggregate models. However, in the nonfreeway models, the parameter for design exceptions was statistically significant and positive for possible injury in the model with property damage only as the base case (p-value of 0.035). The design exception parameter was also statistically significant and negative for nonincapacitating injury in the nonfreeway model with possible injury as the base case (p-value of 0.010). In all other cases, the design exception parameter was not statistically significant (p-values ranging from 0.184-0.710).

Results of the multinomial logit estimation are illustrated in practical format for interpretation in Figure 8, Figure 9, and Figure 10. These figures were developed by setting the values for all variables in the KABCO logit models to their average except for the design exception variable, which was coded as either ‘zero’ (no design exceptions) or ‘one’ (one or more design exceptions). Keeping in mind that there are confidence intervals for the estimates of the parameter values for the design exception variable and that most of the estimates are not statistically significant, the conclusion is that the presence of a design exception does not negatively influence the severity of a crash, should a crash occur.

Parameter estimates for the indicator variable for design exceptions for each of the models, along with the associated p-values, are shown in Table 29. All coefficients

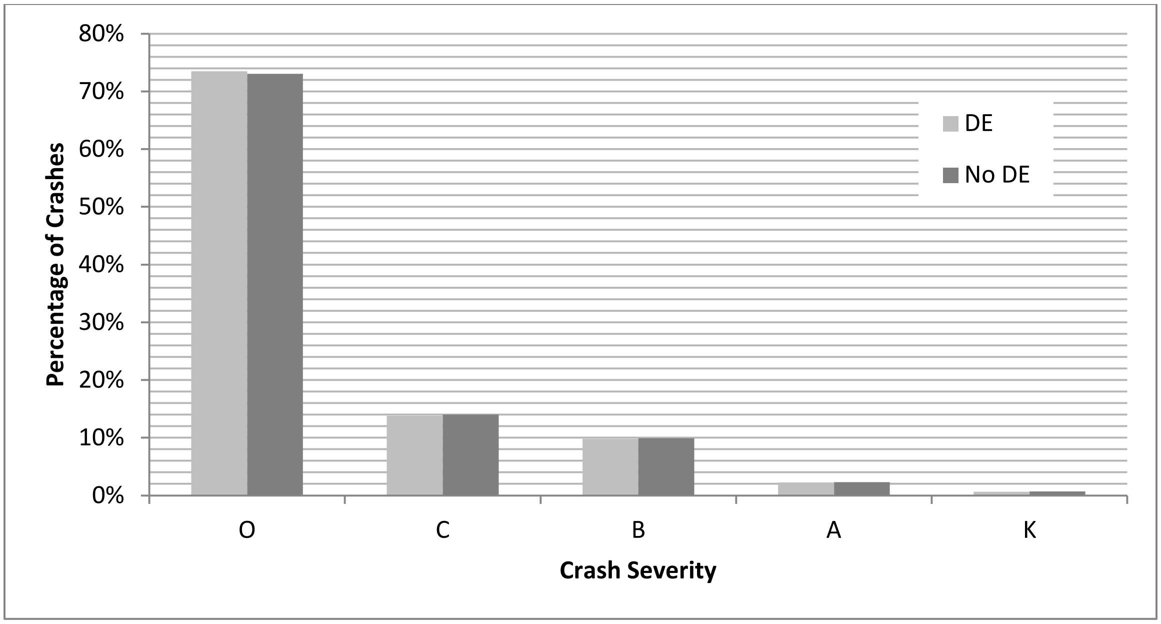

Figure 8 Severity distributions on road segments with and without design exceptions based on crash severity models for aggregate freeway and nonfreeway data (K = fatal; A = incapacitating injury; B = nonincapacitating injury; C = possible injury; O = property damage only)

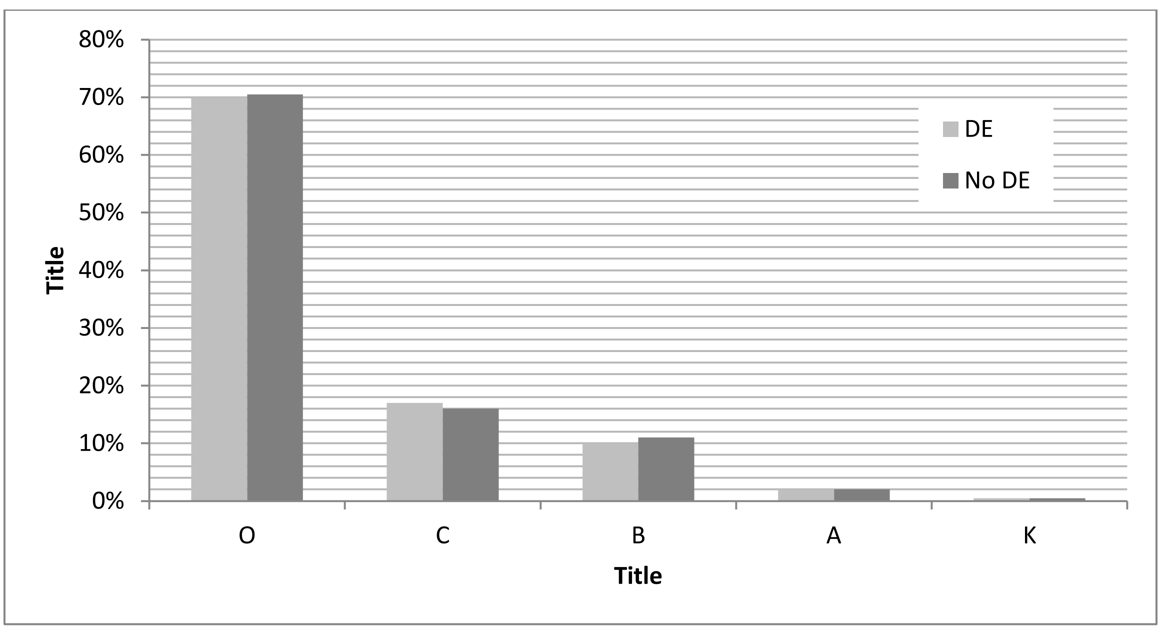

Figure 9 Severity distributions on road segments with and without design exceptions based on crash severity models for nonfreeway segments (K = fatal; A = incapacitating injury; B = nonincapacitating injury; C = possible injury; O = property damage only)

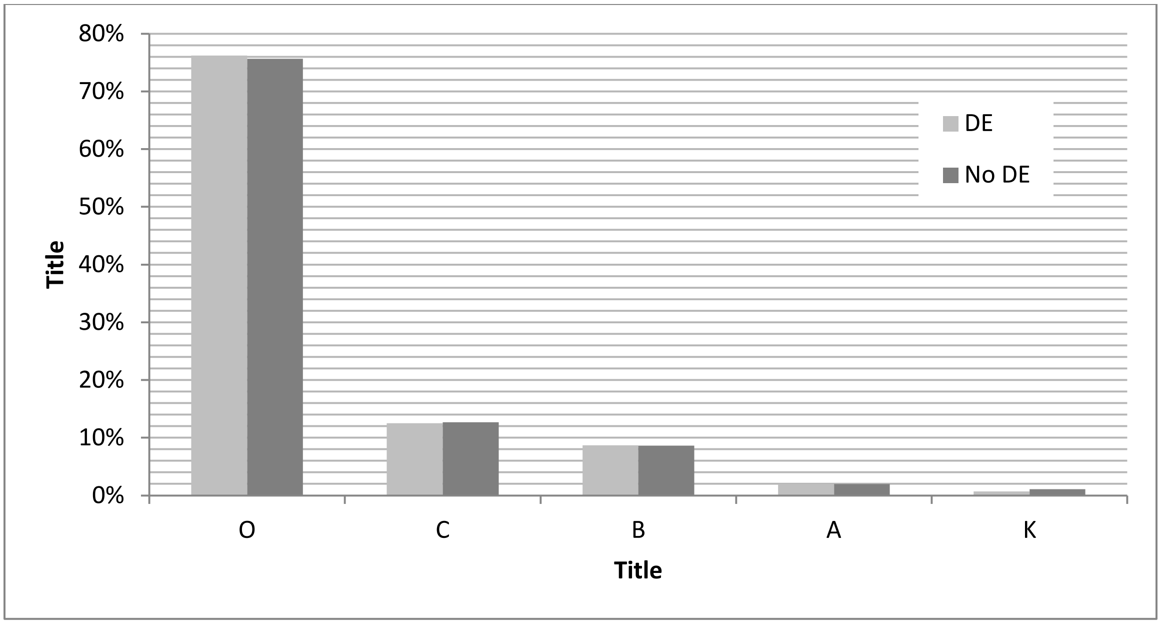

Figure 10 Severity distributions on road segments with and without design exceptions based on crash severity models for freeway segments (K = fatal; A = incapacitating injury; B = nonincapacitating injury; C = possible injury; O = property damage only)

Table 29 Coefficients and p-values for design exception variable in multinomial logit crash severity models

Model	Aggregate All Severities		Aggregate No PDO	
Severity	Coefficient	P-value	Coefficient	P-value
Possible Injury	-0.080	0.047	-	-
Nonincapacitating Injury	-0.068	0.177	0.018	0.765
Incapacitating Injury	-0.122	0.245	-0.033	0.769
Fatal	-0.268	0.162	-0.203	0.330
Model	Nonfreeway All Severities		Nonfreeway No PDO	
Severity	Coefficient	P-value	Coefficient	P-value
Possible Injury	0.249	0.035	-	-
Nonincapacitating Injury	-0.197	0.184	-0.45	0.01
Incapacitating Injury	0.140	0.656	-0.123	0.71
Fatal	1.010	0.202	0.747	0.349
Model	Freeway All Severities		Freeway No PDO	
Severity	Coefficient	P-value	Coefficient	P-value
Possible Injury	-0.102	0.281	-	-
Nonincapacitating Injury	0.091	0.219	0.206	0.043
Incapacitating Injury	-0.049	0.764	0.057	0.742
Fatal	-0.490	0.122	-0.364	0.253

are relative to a 'base case'. The 'base case' for each of the models is either property damage only (for the all severity models) or possible injury (for the fatal-plus-injury models). Signs of the parameter estimates, when looked at in isolation, indicate the possibility of less severe crashes on road segments with design exceptions in the aggregate and freeway models (all severities) and the aggregate fatal-plus-injury model.

The signs of the parameter estimates, looked at in isolation, indicate the possibility of more severe crashes in the nonfreeway models and the freeway model for fatal-plus-injury crashes. When the magnitude and statistical significance of the parameters are considered in addition to the parameter signs, the results indicate no likely difference in the overall severity distribution of crashes occurring on roads with one or more design exceptions when compared to roads without design exceptions. The only statistically significant estimates for the design exception parameter are for the following:

1. The aggregate, all severities model, for possible injury. A negative sign.
2. The nonfreeway, all severities model, for possible injury. A positive sign.
3. The nonfreeway, fatal-plus-injury model. A negative sign.
4. The freeway, fatal-plus-injury model. A positive sign.

These parameter estimates are not consistent, and it should be remembered that the aggregate and freeway models have a high probability of having selection bias. Thus, these results should be interpreted cautiously.

CONCLUSIONS

Summary

State DOTs develop designs and prepare plans for road construction. Designers are guided by a set of state-adopted standards and policies that include design criteria. Design criteria are based on research and practice, and are generally expressed as minimums, maximums, or ranges of values for design elements (e.g., minimum horizontal curve radius, maximum grade). Meeting all design criteria is not always possible or practical. There are cases where meeting all design criteria would result in significant environmental impacts, community impacts, and/or construction costs. When this occurs, a design exception may be explored as an alternative. The potential safety implications of design exceptions are a central issue to design exception review and approval, but documentation of the process by which safety is considered varies from state to state. A survey of state departments of transportation indicated that safety analysis methods varied *(7)*. A literature review conducted as part of this project showed that attempts to analyze the safety performance of locations with design exceptions were limited.

The objective of this research was to compare safety, measured by expected crash frequency and severity, on road segments where design exceptions were approved and constructed to safety on similar road segments where no design exceptions were approved or constructed. The project used data from the State of Utah. Data were collected for design exceptions constructed in Utah in the years 2001 through 2006. Design exception request and approval forms, Google Earth, Google Street View, UDOT functional classification maps, and UDOT traffic volume data were used to identify and define road segments with and without design exceptions. Ultimately, a total of 48 segments with design exceptions and 132 segments without design exceptions were used for analysis. Propensity scores were applied in this study to assess the selection of comparison sites (i.e., sites without design exceptions) and decrease the chance of selection bias. The propensity score analysis indicated that there was likely minimal, if any, selection bias in the nonfreeway data. The analysis indicated that there were selection bias issues with the freeway data. Additional data collection was not able to address the selection bias in the freeway data due to the limited number of additional urban freeway segments in Utah.

Design exception effects on expected crash frequency were quantified using a negative binomial regression modeling. This approach used two different approaches. The first approach used an indicator variable for the presence of design exceptions (0 = no design exception, 1 = the presence of one or more design exceptions). The second approach was the use of a transferability test that tests if parameter estimates from a model using only road segments with design exceptions are transferable with parameter estimates from a model using only road segments that do not have design exceptions. Parameter estimates for the first approach indicated that road segments with one or more design exceptions had the same expected frequency of total crashes (all types and severities), fatal-plus-injury crashes, and property-damage-only crashes as road segments without design exceptions. The transferability test indicated that the parameters were not transferable, indicating that either 1) design exceptions may influence crash frequency, or 2) characteristics on road segments with design exceptions differ in how they affect crash frequency than on road segments without design exceptions. The second option is a likely explanation of the results. The results for the transferability test were consistent with the Indiana study *(6)*.

Design exception effects on expected crash severity were quantified using three approaches: 1) computing severity distributions at locations with and without design exceptions, 2) estimating separate negative binomial regression models by severity level, and 3) estimating multinomial logit models. The results of the first method showed that crashes on road segments with design exceptions tend to be less severe than crashes on road segments without design exceptions for the aggregate and freeway data. The opposite is true for the nonfreeway data. However, this first approach was not able to capture additional differences between road segments with and without design exceptions that may also impact the crash severity distributions. The latter two methods addressed this limitation; results indicated no difference in the severity distribution of crashes occurring on roads with one or more design exceptions when compared to crashes occurring on roads without design exceptions.

Findings

Propensity Score Analysis

Propensity scores were effective in assessing the selection of comparison sites (i.e., sites without design exceptions). Propensity scores for the nonfreeway segments showed that the treatment and comparison sites were well-matched. For the freeway segments, there were significant differences in the propensity scores for treatment and comparison segments. This meant that there are likely selection bias issues for freeway segments (i.e., freeway segments with design exceptions were inherently different than freeway segments without design exceptions). A larger sample of urban freeway segments would be required to overcome the selection bias issues with the freeway segments. The analysis would have to be expanded to include freeway segments outside of Utah as the entire urban freeway system in Utah was included in the analysis.

Crash Frequency

Road segments with one or more design exceptions had the same expected frequency of total crashes (all types and severities), fatal-plus-injury crashes, and property-damage-only crashes as road segments without design exceptions for the aggregate and nonfreeway models. The freeway models indicated that there may be differences in expected crash frequencies between segments with and without design exceptions; the estimated differences were statistically significant to approximately the 90^{th} percentile. However, the freeway segment results are likely impacted by the selection bias issues described above and may not reflect the actual impacts of design exception presence on crash frequency. These findings were based on:

a. Parameter estimates for negative binomial regression models estimated using data from both freeways and nonfreeways with variables that captured the expected differences in safety performance between these facility types.

b. Parameter estimates for negative binomial regression models estimated using data from nonfreeway road segments.

c. Parameter estimates for negative binomial regression models estimated using data from freeway road segments.

The plotted model relationships indicate that for nonfreeway road segments and low traffic volume freeway segments (typically in rural areas), the presence of design exceptions does not impact safety. However, the difference in safety performance of high-volume freeway segments with and without design exceptions remains unknown. The current findings do not imply that there should be an increase or decrease in design exceptions granted on any road segment or that the process should be changed. The results do imply that the UDOT design exception process, during the years 2001-2006, was effective for nonfreeway road segments.

Separate negative binomial models for locations with and without design exceptions on nonfreeway road segments did not yield parameter estimates that were transferable from the locations with design exceptions to the locations without design exceptions. This may be due to 1) design exceptions do, in fact, affect crash frequency, or 2) the characteristics on road segments with design exceptions affect crash frequency differently from road segments without design exceptions.

Crash Severity

There were no differences in the severity distributions of crashes occurring on roads with one or more design exceptions when compared to crashes occurring on roads without any design exceptions. This finding was based on parameter estimates for a series of negative binomial regression models separated by severity level as well as parameter estimates for multinomial logit models (with and without property damage only crashes included). Models were estimated using "pooled" data from both freeways and nonfreeways with variables that capture the expected differences in safety performance between these facility types, from nonfreeway data only, and from freeway data only.

The findings of this study show that the UDOT design exception review and approval process, as implemented in years 2001 through 2006 on nonfreeway road segments, was effective from a safety perspective. Findings are not intended to support approving a greater number of design exceptions or fewer design exceptions.

Limitations and Challenges

Data elements available to characterize treatment and comparison segments were limited to those identified in Table 5. Additional detail on horizontal alignment (e.g., curve radius, superelevation) and vertical alignment (e.g., grade, rate vertical curvature) would be desirable, but could not be practically collected within the project scope and budget. UDOT's Projectwise System was used to try and find data on these design elements, but design information or drawings for the majority of the road segments could not be located.

The comparison segments were defined, when possible, within the same project boundaries as the project with the design exception, but at locations without any design exceptions. This was done to maximize similarity between the treatment and comparison segments and also ensure that the comparison locations did not have design exceptions on them (otherwise, they would be identified in the project documents). Locations along the same route and in near proximity to the project segment were identified as comparison segments when the first approach was not possible. UDOT's Projectwise System was used to try and find as-built plans at these secondary locations to confirm that all elements met design criteria. This was not always possible, so the available data sources (e.g., Google Earth, Google Street View) were used to confirm that design elements met criteria. Some design elements could not be directly measured in the available data sources (e.g., superelevation, grade, rate of vertical curvature).

There was a significant difference in the propensity scores for treatment and comparison segments on freeways. The freeway segments in the treatment and comparison groups covered all of the urban freeways in Utah and some rural freeway segments. Due to a lack of additional freeway segments to choose from in urban areas, nothing additional could be done to balance out the propensity scores for the freeway segments. This means that there may be selection bias issues for freeway segments.

RECOMMENDATIONS

This report presented a unique study on the safety impacts of design exceptions; only one other similar effort was identified *(6)*. As with any observational study, a possibility of confounding effects from extraneous variables always exists and can never be completely excluded. The use of propensity scores attempts to account for and balance extraneous variables but does not guarantee that the effects from them are completely removed. Recommendations for future work are provided below.

Other Modeling Techniques

Other modeling methods that could be explored are the following.

Other Model Estimators

Expand the current cross-sectional analysis to explore other model estimators, including the mixed multinomial logit model and the random parameters negative binomial model. These methods were successfully employed in the Indiana study *(6)*. The mixed multinomial logit and in the random parameters negative binomial model allow for site-to-site variation and have the potential to yield estimates of the effects of design exceptions that are more accurate and precise. This is true for both standard, cross-sectional models and longitudinal models.

Longitudinal (Panel) Models

Explore the use of longitudinal negative binomial and logistic regression for analysis of the data using more years of crash data. This would take into account both the cross-sectional and time-series attributes of the data. This can also reduce omitted variable bias if it is present in the cross-sectional models. The use of longitudinal models is limited if the road segments do not change over time. For example, if the value of a variable does not change over time, only random parameters longitudinal models can be used if a parameter for that variable needs to be estimated. Thus, in order to get the most from longitudinal models, data from before and after a design exception were constructed on a road segment would be required.

Variable Interactions

As discussed in the crash frequency findings, the parameters from a model with only design exception data were not transferable to locations without design exceptions. One of the possible explanations was that the characteristics of road segments with design exceptions impact crash frequency differently than on road segments without design exceptions.

This explanation could be explored using variable interactions. Exploring the safety impacts of design exceptions by using interactions between the indicator variable for design exceptions and other independent variables is recommended. This could reveal interesting differences in the outcomes for attributes between locations with design exceptions and locations without design exceptions. Examples such as interactions between design exceptions with traffic volume, design exceptions with percent single trailer large trucks, design exceptions with percentage combo trucks, and design exceptions with any other predictor variable could yield additional insight into safety outcomes. As mentioned previously, this could reveal the reasons for the findings of both this study and the Indiana study that the models for locations with design exceptions and the models for locations without design exceptions are not transferable.

Measurement Error Models

Use measurement error models to minimize possible bias due to measurement error. Possible sources of error could include traffic volume and the presence of a design exception on a road segment. It is possible that some of the comparison sites could have a design exception unless as-built plans or other documentation can be found to show that it was constructed without design exceptions. These sources of error could be accounted for using measurement error models. Measurement error models that could be used in a study on the safety impacts of design exceptions include linear measurement error models, nonlinear measurement error models (bayesian statistics and simulation methods), and the difference-in-differences propensity score analysis method.

Freeway Segments

In the United States, the freeway system is aging and traffic demand is increasing. For these reasons, much of the existing freeway system will require reconstruction in the near future. As design requirements have changed and the land surrounding urban freeways has become heavily used, future reconstruction will have large costs in terms of environmental impacts, social impacts, and finances in order to meet design requirements. It is likely that as this reconstruction happens, design exceptions will be sought as an alternative to offset these costs. As it has been shown in this project that the available data for analysis of design exceptions on freeways had a high probability of bias, there is need for further research on the safety impacts of design exceptions on freeways. It is recommended that:

1. For the state of Utah, continue to expand the dataset to include additional treatment and comparison locations and additional years of crash data. Given that all Utah urban freeways were included in the dataset, additional years of crash data combined with time-series and panel data analysis approaches appear to be the most practical option.

2. For other states to follow the process outlined in this study as well as the methods discussed in the recommendations and conduct research into the safety impacts of design exceptions on freeways.

It is also recommended that these steps should be done on nonfreeway roads with design exceptions. This further research for all facility types could use the recommended methods described above.

Liability

It has been pointed out that if a state DOT is sued for negligence due to the presence of a design exception, a jury is more likely to be forgiving if small rather than great deviation and of a single rather than multiple design exceptions were granted *(13)*. For this reason it is recommended that future research on design exceptions look at the safety impacts for single design exceptions, multiple design exceptions, and specific combinations of design exceptions. Effects on specific crash types (e.g., single-vehicle; multiple-vehicle) should also be explored.

Crash Modification Factors

Future work should be done in such a way that CMFs for design exceptions can be produced and compared to CMFs that have been created for the related design elements. This could be done using the different research methods previously described in the recommendations and using the results to compute the crash modification factors. However, this should only be done using studies with large samples. Also, a case-control study methodology could also be explored as a way to create CMFs for design exceptions *(43).* The case-control methodology essentially requires that for each location with a design exception, a location that is similar in characteristics (not including the design exception) be found and used for comparison (similar to the approach described in this thesis).

REFERENCES

1. AASHTO. *A Policy on Geometric Design of Highways and Streets.* American Association of State Highway and Transportation Officials, 2004.

2. UDOT. *Roadway Design Manual of Instruction.* Salt Lake City., 2007.

3. UDOT. *Design Exception and Design Waiver Form.* Salt Lake City, UT : Utah Department of Transportation, 2009.

4. FHWA. *Federal Aid Policy Guide, Subchapter G - Engineering and Traffic Operations, Part 625 - Design Standards for Highways.* FHWA, U.S. Department of Transportation, 1997.

5. Stamatiadis, N., Agent, K.R. and Pigman, J.G. *Design Exceptions and Safety.* 2005, Compendium of Papers for the 3rd International Symposium on Highway Geometric Design.

6. Malyshkina, N. and Mannering, F. Emperical Assessment of the Impact of Highway Design Exceptions on the Frequency and Severity of Vehicle Accidents. 2010, *Accident Analysis and Prevention*, Vol. 42(2), pp. 131-139.

7. Mason, J.M. and Mahoney, K.M. *Design Exception Practices.* Transportation Research Board of the National Academies, Washington D.C., 2003, NCHRP Synthesis 316.

8. AASHTO. *Highway Safety Manual.* American Association of State Highway and Transportation Officials, 2010.

9. Porter, R. J. and Jonathan, J. S. *Safety Impacts of Design Exceptions in Utah.* Salt Lake City : Utah Department of Transportation, 2012.

10. Porter, R. J. and Wood, J. S. *Safety Impacts of Design Exceptions in Utah.* Mountain Plains Consortium, 2012.

11. Stein, W.J. and Neuman, T.R. *Mitigation Strategies for Design Exceptions.* Chicago, IL : FHWA. U.S. Department of Transportation, 2007, FHWA-SA-07-001.

12. AASHTO. *A Policy on Design Standards - Interstate System.* American Association of State Highway and Transportation Officials, 2005.

13. Martin, S.F.J. *Design Exceptions: Legal Aspects.* Transportation Research Board of the National Academies, Washington D.C., 1994, Transportation Research Record: Journal of the Transportation Research Board, Vol. 1445, pp. 156-159.

14. Hauer, Ezra. *Obervational Before-After Studies In Road Safety.* Kidlington, Oxford, UK : Elsevier Science, 2002.

15. Bonneson, J., Zimmerman, K. and Fitzpatrick, K. *Roadway Safety Design Synthesis.* College Station : Texas Transportation Institute, 2005. FHWA/TX-05/0-4703-P1.

16. Bonneson, J. and Pratt, M.P. *Roadway Safety Design Workbook.* College Station : Texas Transportation Institute, 2009. FHWA/TX-09/0-4703-P2.

17. FHWA. Crash Modification Factors Clearinghouse. [Online] June 20, 2012. http://www.cmfclearinghouse.org/.

18. Lord, D. and Bonneson, J.A. *Role and Application of Accident Modification Factors (AMFs) within the Highway Design Process.* Transportation Research Board of the National Academies, Washinton D.C., 2006, Transportation Research Record: Journal of the Transportation Research Board, No. 1961, pp. 65-73.

19. Guo, Shenyang and Fraser, Mark W. *Propensity Score Analysis.* Thousand Oaks, California : Sage Publications, Inc., 2010.

20. Shadish, William R., Cook, Thomas D. and Campbell, Donald T. *Experimental And Quasi-Experimental Designs For Generalized Causal Inference.* Bostin : Houghton Mifflin, 2002. p. Bostin.

21. Rosenbaum, Paul R. *Observational Study.* 2005, Encyclopedia of Statistics in Behavioral Science, pp. 1451-1462.

22. Hauer, E. Cause, Effect and Regression in Road Safety: A Case Study. 2010, *Accident Analysis and Prevention*, Vol. 42, pp. 1128-1135.

23. Tarko, A., Eranky, S. and Sinha, K. *Methodological Considerations in the Developement and Use of Crash Reduction Factors.* 1998, Presented at the 77th Annual Meeting of the Transportation research board, Washington D.C.

24. Washington, Simon P., Karlaftis, Matthew G. and Mannering, Fred L. *Statistical And Econometric Methods For Transportation Data Analysis Second Edition.* Boca Raton : Chapman & Hall/CRC, 2011.

25. Lord, D. and Mannering, F. *The Statistical Analysis Of Crash-Frequency Data: A Review And Assessment Of Methodological Alternatives.* 2010, Transportation Research Record, Vol. 44, pp. 291-305.

26. Kennedy, Peter. *A Guide To Econometrics.* Malden, MA, USA : Blackwell Publishing, 2008.

27. Frees, Edward W. *Longitudinal And Panel Data: Analysis And Applications In The Social Sciences.* Cambridge, UK : Cambridge University Press, 2004.

28. Cochran, W.G. The Effectiveness of Adjustment by Subclassification in Removing Bias in Observational Studies. 1968, *Biometrics*, pp. 205-213.

29. Arpino, Bruno and Mealli, Fabrizia. The Specification of the Propensity Score in Multilevel Observational Studies. 2011, *Computational Statistics and Data Analysis*, Vol. 55, pp. 1770-1780.

30. Jovanis, P.P. and Chang, H.L. Modeling the Relationship Between Accidents and Miles Traveled. *Transportation Research Board of the National Academies, 1986, Transportation Research Record: Journal of the Transportation Research Board,* Vol. 1068, pp. 42-51.

31. Miaou, S.P. The Relationship Between Truck Accidents and Geometric Design of Road Sections: Poisson versus Negataive Binomial Regressions. 1994, *Accident Analysis and Prevention*, Vol. 26(4), pp. 471-482.

32. Milton, J.C., Shankar, V.N. and Mannering, F.L. Highway Accident Severities and the Mixed Logit Model: An Exploratory Emperical Analysis. 2008, *Accident Analysis and Prevention*, Vol. 40, pp. 260-266.

33. Shankar, V. and Mannering, F. An Exploratory Multinomial Logit Analysis of Single-Vehicle Motorcycle Accident Severity. 1996, *Journal of Safety Research*, Vol. 27, pp. 183-194.

34. Shankar, V., Mannering, F. and Barfield, W. Statistical Analysis of Accident Severity on Rural Freeways. 1996, *Accident Analysis and Prevention*, Vol. 28, pp. 391-401.

35. Khattak, A., Kantor, P. and Council, F. Role of Adverse Weather in Key Crash Types on Limited-Acces Roadways: Implications For Advanced Weather Systems. Transportation Research Board of the National Academies, Washington D.C., 1998, *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1621, pp. 10-19.

36. Savolainen, P. T., et al. The Statistical Analysis of Highway Crash-Injury Severities: A Review and Assessment of Methodological Alternatives. 2011, *Accident Analysis and Prevention*, Vol. 43, pp. 1666-1676.

37. Hausman, J. and McFadden, D. Specification Tests for the Multinomial Logit Model. 1984, *Econometrica*, Vol. 52, pp. 1219-1240.

38. Caliendo, M. and Kopeing, S. Some Practical Guidance for the Implementation of Propensity Score Matching. 2008, J*ournal of Economic Surveys*, Vol. 22(1), pp. 31-72.

39. Dehejia, Rajeev H. and Wahba, Sadek. Propensity Score-Matching Methods For Nonexperimental Causal Studies. 2002, *The Review of Economics and Statistic*s, pp. 151-161.

40. Kenneth, T. *Discrete Choice Methods with Simulation.* Cambridge : Cambridge University Press, 2009.

41. Heckman, J. J., Ichimura, H. and Todd, P. E. Matching As An Econometric Evauation Estimator. 1997, *Review of Economic Studies*, pp. 605-654.

42. Park, Peter Young-Jin and Saccomanno, Frank Fedel. Reducing Treatment Selection Bias for Estimating Treatment Effects Using Propensity Score Method. 2007, *Journal Of Transportation Engineering*, pp. 112-118.

43. Gross, F. and Donnell, E. A Comparison of Cross-sectional and Case-Control Methods in Traffic Safety Research. 2011, *Journal of Safety Research*, Vol. 42, pp. 117-129.